Improving the Efficiency of Agricultural Development:

Can farmer typologies be used to predict the adoption of agricultural innovations for the poorest farmers, and therefore, increase the impact of rural development programs on the rural poor?

Supervisor:
Dr. Andrew Wyatt

Candidate Number:
13716

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Declaration

This dissertation contains no plagiarism, has not been submitted in whole or in part for the award of another degree, and is solely the work of candidate 13716

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Signed: (candidate 13716)

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Abstract

This investigation, through a literature review, outlines how agricultural development is an effective tool for achieving the goals of human development theory, the participatory approach to development and the sustainable development approach. In this investigation, sustainable intensification is identified as an essential part of agricultural development. Through an examination of the literature, it is made clear that there is a low adoption rate for agricultural innovations, this inhibits sustainable intensification. Moreover, it is demonstrated that the distribution of agricultural innovations favours wealthier farmers, who are less deterred by the perceived risk associated with the adoption process. Antecedent research has tried to improve adoption rates by targeting particular groups of farmers, known as farmer typologies. Traditional typologies focus on the structural characteristics of farms, such as farm size, crop diversity and livestock diversity. Despite the use of these typologies, adoption rates remain low. An emerging method for creating typologies incorporates the personal motivations and attitudes of farmers, however, these have not been empirically tested in relation to the real-life adoption of innovations.

This investigation used data from the Africa Research In Sustainable Intensification for the Next Generation (RISING) project based in the Ethiopian Highlands to investigate three types of typology. The ultimate aim of this investigation was to see whether a particular set of typologies can be used to identify high adopting farmers in the lowest wealth quartiles. The first set of typologies is based solely on the structural characteristics of the farms surveyed. The second set of typologies is solely based on motivational characteristics. The third set of typologies is based on both structural and motivational characteristics. Two variables are used to measure adoption: Adoption rate, which indicates the percentage of innovations which farmers continued to use after phase one of the Africa RISING program; Adoption strength, which measures how strongly farmers have adopted each innovation.

The results of this investigation indicate that there is sufficient evidence to support the use of all three sets of typologies to predict high adoption rates and high adoption strength in farmers. However, there is insufficient evidence to support the use of structural clusters for predicting high adoption rates, or adoption strength, for farmers in the lowest wealth quartiles. There is also insufficient evidence to support the use of motivational typologies to predict high adoption rates for farmers in the lowest wealth quartiles. In contrast, the results indicate that motivational typologies could effectively predict high adoption strength for farmers in each individual wealth quartile. There was sufficient evidence to suggest that combined typologies could be used to predict high adoption rates and high adoption strength for farmers in the lowest wealth quartiles.

This research shows the promise of using motivational characteristics to group farmers. This investigation should encourage further research which investigates how motivational typologies can be operationalised in order to catalyse sustainable intensification and make agricultural innovations more accessible to the rural poor.

List of Acronyms and Abbreviations

- ANOVA – Analysis of Variance
- FA – Food Availability
- FAO – Food and Agricultural Organisation of the United Nations
- GDP – Gross Domestic Product
- GNP – Gross National Product
- IFPRI – International Food Policy Research Institute
- ILRI – International Livestock Research Institute
- MV – Modern Variety
- PAM – Partitioning Around Medoids
- PCA – Principal Component Analysis
- PPP – Purchasing Power Parity
- RISING - Research In Sustainable Intensification for the Next Generation
- SDGs – Sustainable Development Goals
- SSA – Sub-Saharan Africa
- TVA – Total Value of Activities
- UN – United Nations
- UNDP – United Nations Development Program

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1. Introduction

In 2016 it was estimated that 10.7 percent of the global population live below the international poverty line of US$1.90 per day and 795 million people suffer from chronic hunger (Cuesta *et al.*, 2016, 4; Jahan, 2016, 30). The vast majority of these people live in low-income and lower-middle-income countries, where the population is expected to grow from 3.5 to 4.5 billion by 2030, placing further strain on existing resources (Bertini *et al.*, 2017, v). With only 12 years before the 2030 deadline, effective action must be taken in order to meet the Sustainable Development Goals (SDGs) in a growing population.

The first SDG relates to the need to "end poverty in all its forms everywhere" (Jahan, 2016, 46). To date, significant progress has been made, as outlined by the 2016 World Bank "Poverty and Shared Prosperity" Report (Cuesta *et al.*, 2016, 35-38). According to the report, there were 1.1 billion fewer people living below the poverty line in 2013, compared to 1990, despite a 1.9 billion increase in population. Meaning approximately 50 million people have been lifted out of poverty every single year. Although this is an immense achievement, many are concerned by the uneven rates of development (African Development Bank, 2012, 40; Herdt, 2010, 3257; Jahan, 2016, 1).

Certain regions are more poverty-stricken than others. Sub-Saharan Africa (SSA) is the only region where the number of people living below the poverty line has increased between 1990 and 2013 (Cuesta *et al.*, 2016, 35-38). As well as having the largest population below the poverty line, with 50.7 percent of the worlds impoverished population, SSA also has the largest poverty gap, meaning that the poor in SSA are further below the poverty line, compared to other regions (Cuesta et al., 2016, 36).

The most acute poverty generally hits rural areas. The majority of those living below the 2011 Purchasing Power Parity (PPP) line work in agriculture and live in rural areas (Cuesta et al., 2016, 6). According to Chambers (1978, 209-210), the rural poor are the least likely to benefit from government services and development programs, due to the fact that communities are often less organised and difficult to access using communication technologies. Importantly, in low-income and lower-middle-income countries, small farms (less than 2 hectares) dominate. A study from 2004 found that these small farms contained 92 percent of the world's "dollar poor", those who earn less than $1 per day (Lipton, 2005, vii).

To determine the best way to provide efficient support to poor communities so that they can develop a sustainable livelihood, it is necessary to first investigate more thoroughly the connections between agriculture and development. Section 2 of the present investigation outlines the definitions of development used herein. By employing the perspectives of human development, participatory approaches to development and sustainable development approaches, it is shown that the sustainable intensification of agricultural production effectively empowers and enlarges the choices of smallholder farmers. Section 2 explains that low adoption rates are a barrier to sustainable intensification and reviews the literature concerning adoption rates.

This review highlights two key components of the debate. Firstly, the distribution of agricultural innovations favours wealthier farmers who are less risk averse. Secondly, that the success of an agricultural innovation at the earliest stages of intervention can increase the likelihood that technologies will diffuse horizontally between smallholder farms. As a result, agricultural interventions must be targeted to high adopting farmers, increasing the chances that they will diffuse horizontally between smallholder farms. As is demonstrated in section 2.2, many programs identify high adopting farmers through the use of typologies. Current typologies are based around the structural characteristics of farms. This does not account for the heterogeneity of smallholder farms. It is deduced, based on this literature, that incorporating farmers' personal motivations into typologies is a promising improvement on current methods. It is demonstrated that further research is needed in order to test how these personal motivations can be used to identify high adopting farmers.

Based on the discussion in section 2, section 3 specifies the precise aim of this investigation. The goal is to empirically test how data about farmers' motivations can be used to predict high adoption rates. More specifically, this investigation seeks to find a group of high-adopting farmers who are in the lowest wealth quartiles. Section 4 describes the method used to empirically test this, drawing on data from the Ethiopian highlands, provided by the International Livestock Research Institute (ILRI). This data, collected in relation to the Africa RISING program, was gathered after smallholder farms were provided with agricultural innovations. By using "Partitioning Around Medoids" (PAM) clustering, this investigation creates three different types of typologies, also referred to as clusters. The first set of clusters, "structural clusters", is solely based on structural characteristics of smallholder farms. The second set of clusters, "motivational clusters", is based solely on the personal motivations of the farmer. Finally, the third set of clusters is based on both structural and motivational clusters. Accordingly, they are given the name of "combined clusters".

Section 5 shows the results of this analysis, explaining in what way the use of one typology or another can help identify farmers who will adopt innovations, implement them efficiently and therefore encourage other farmers applying them, hereby spreading their application. This analysis is based primarily on two variables: adoption rate, which measures the percentage of technologies which farmers continued to use; adoption strength, which measures strongly farmers committed to a particular innovation. Concerning structural typologies, there is insufficient evidence to support that they are able to identify high adoption rates for farmers in the lower wealth quartiles. Concerning motivational clusters, it is shown that there is insufficient evidence to support that they help to identify farmers with high rates of adoption in the lower wealth quartiles. However, there is sufficient evidence to support that these motivational clusters are able to identify farmers with a strong commitment to selected technologies in the lower wealth quartiles. Moreover, the use of combined clusters to identify farmers with high adoption rates and a strong commitment to selected technologies is promising. Significant relationships between adoption rates and combined clusters were found for the lower wealth quartiles. This was also the case for adoption strength.

As is outlined in section 6, this investigation is designed to demonstrate the promise of these techniques. It is proposed that more rigorous testing will lead to the development of more robust typologies. These can be used to catalyse sustainable intensification in SSA. As outlined in section 2, this can help achieve the goals of human development.

2. Literature Review on Development Theories and their Application to Agricultural Development

Based on the problems outlined in section 1, it is clear that development programs must urgently step up their efforts to fight against the extreme poverty prevalent in rural areas of developing countries. This section uses the perspectives given by human development theory, which incorporates the participatory approach and the sustainable development paradigm, as a baseline from which to explain the merits of agriculture-led development strategies. An overview of these strands of development also provides a useful foundation from which to examine the real-world implementation of agriculture as a tool for development. Through this examination it is made clear that low adoption rates of new agricultural innovations impede development. Through a literature review, the various factors thought to influence these adoption rates are investigated, providing the basis for the empirical investigation outlined in sections 3, 4 and 5. In accordance with the principles of human development, sustainable development approaches and participation approaches, it is shown that improving the uptake of new agricultural technologies opens a sustainable pathway for enlarging the choices of some of the world's most marginalised communities.

2.1 Defining the goals of development

First defined in the 1990 United Nations Human Development Report, human development is a process of enlarging people's choices (ul Haq et al., 1990, 10). These choices not only encompass basic needs, but also additional choices which are highly valued in many societies. Basic needs include the ability to: access the necessary resources for a decent living standard; lead a long and healthy life; acquire knowledge. "Additional choices" involve; enjoying personal self-respect and guaranteed human rights; political, economic and social freedom; opportunities for being creative and productive. To many, the importance of these principles may appear obvious. However, this was one of the development paradigms that provided alternatives to ideas that had dominated since the 1950s (Ellis and Biggs, 2001, 439). Previously, economic growth was considered synonymous with social welfare (van den Bergh and Antal, 2014, 2). This was based on the assumption that enlarged choices would follow automatically from increases in gross national product (GNP), leading to the widespread use of the concept of trickle-down economics. An approach based on such a concept ignored many major issues, such as poverty and malnutrition, which human development theory seeks to address (ul Haq et al., 1990, 104). In short, human development categorises economic growth as a potential tool for development, but not the central aim.

Human development theory was cultivated in an environment critical of market fundamentalism in development, that is to say, an exclusively market-based approach to development. Consequently, it incorporated many of the principles of antecedent alternative theories. Participatory approaches also arose in a similarly alternative environment, advocating for development strategies that involved referents, the beneficiaries of development programs, in the decision making progress. In 1979, Chenery led the creation of an influential critique of market fundamentalism entitled "Redistribution with Growth", the foundation of the basic needs approach to development (Chenery, Jolly, Ahluwalia, Bell, and Duloy, 1979, xiii). This report problematised market-based approaches to development. It stressed that the benefits of economic growth, for developed countries, had not reached a third of their population. It also emphasised the need for more targeted interventions, directly addressing the characteristic issues faced by the rural and urban poor (Chenery et al., 1979, xvii; 113; 136). This rhetoric was emblematic of the shift towards participatory development, emphasising that the "poorest of the poor" should be empowered. This approach promoted the active involvement of the referents of development. As a result of this shift, it became difficult for development projects to procure funding without some mention of participatory approaches (White in Michener, 1998, 2105). It is therefore unsurprising that the first Human Development Report emphasised the importance of participation and empowerment (ul Haq et al., 1990, 28-29).

Sustainable development also emerged as an alternative approach to market fundamentalism. It first gained serious traction following the publication of the Club of Rome's "Limits to Growth" report, which generated scepticism towards conventional modes of economic growth (Castro, 2004, 196; Meadows, Meadows, Randers, and Behrens Ill, 1971, 23-24). Escobar (1996, 330-331) outlines how sustainable development materialised to ensure that economic growth could continue efficiently with a minimum use of resources. There is a debate in the literature about the origins of sustainable development concepts (Castro, 2004; Escobar, 1996). Despite this debate, one key concept has emerged unscathed, the idea that sustainable development should secure the needs of future generations (ul Haq *et al.*, 1990, 7). Some have used this concept as an argument to encourage economic growth while more radical critical academics have used this idea to promote grassroots development and empowerment (Castro, 2004).

Both human development and participation theories have been selected for the same reason they emerged; they attempt to address the needs of the poorest parts of the population, those who had previously been neglected by the dominant development paradigm. The central idea of sustainable development is universal: development should also secure the rights of future generations. By no means does this investigation suggest that other means of development, such as macroeconomic growth, are unimportant. It merely aims justify the need for more targeted interventions which are directed at the poorest parts of the population

2.2 How agriculture can help achieve the goals of development

This subsection explores how agricultural development strategies can be used to achieve the goals of human development, participatory approaches and sustainable development approaches. More specifically, how sustainable increases in agricultural production can be targeted to benefit the poorest parts of the population. Additionally, the operationalisation of such strategies is investigated, revealing the role that low adoption rates play in impeding development.

It has been established that this research seeks to address the needs of the poorest parts of the populations. As previously mentioned, Lipton (2005, vii) found that 92% of the world "dollar poor" lived in smallholder farms, less than two hectares in area. It therefore seems logical that any effective strategy for poverty alleviation should include plans to target those working on smallholder farms. Indeed, some development programs recognised this in the early 1970s and 1980s, where there was a peak in the amount of development aid allocated towards agriculture (Dethier and Effenberger, 2012, 176). Despite a period of disinterest, development programs have once again emphasised the need for agricultural aid following the 2008 World Development Report (Byerlee *et al.*, 2008; Dethier and Effenberger, 2012, 176). This report outlines that increased agricultural production is essential for mass poverty alleviation and reduced food insecurity, some of the goals outlined by human development theory (Byerlee *et al.*, 2008, 1). Additionally, this report emphasises the unique position of agriculture. Its reliance on nature obliges the encouragement of sustainable practices, ensuring a continuous yield. Finally, the report emphasises the need for participation which empowers small holder farmers through the selection and distribution of new technologies (Byerlee *et al.*, 2008, 172).

Valdés and Foster (2010, 1362) highlight how agriculture is an effective tool for poverty reduction while Lipton (2005, 9) states that "there are virtually no examples of mass poverty reduction since 1700 that did not start with sharp rises in employment and self-employment income due to higher productivity in small family farms". However, it is important to understand how these strategies work in practice, this is best explained through previous examples. Beginning in the late 1960s, many Asian countries experienced unprecedented levels of economic growth accompanied by improved living standards, a phenomenon later labelled as the "East Asian Miracle" (Page et al., 1994, 1). Only a few years before, East Asia, along with Latin America, experienced significant increases in agricultural production known as the "Green Revolution" (Dalrymple, 1975, 3). During this time, greater emphasis was placed on agricultural research in developing countries (Dalrymple, 1975, 3). New crop varieties, fertiliser and other agricultural innovations spread rapidly. Between 1965 and 1973 over 30 million hectares of high-yielding varieties of wheat and rice were planted (Dalrymple, 1975, 19). As a result, average agricultural outputs more than doubled in developing countries and they increased fourfold in East Asia

(Herdt, 2010, 3257). Although a wide variety of strategies contributed to the East Asian Miracle, it is known that increased agricultural production played a significant role (Page *et al*., 1994, 5)

Despite its advantages, the Green Revolution did not escape criticism. The distribution of agricultural innovations often benefited wealthier farmers (Pingali, 2012, 12304). According to Pingali (2012, 12304), poorer farmers were limited by poor access to credit, output markets and insecure ownership of the scarce land they had. Pingali (2012, 12304) also outlines how the benefits of the Green Revolution were reaped by males, a trend which existed across continents and crop varieties. Moreover, the benefits of the green revolution were primarily felt in Asia. After the Green revolution, 82 percent of agricultural land had been planted to modern varieties of crop. While in SSA, only 27 percent of land had been planted to modern varieties (Pingali, 2012, 12302).

One consensus appears in the literature, SSA has not yet experienced a green revolution (Dethier and Effenberger, 2012,183). Today more than ever, new farming techniques and technologies are the primary drivers of increased agricultural production. Seed varieties have been developed that increase crop yields, provide resistance to drought and resistance to disease (Qaim and Zilberman, 2003; Wiggins, Kirsten, and Llambí, 2010, 1342). Such seed varieties, which were not widely adopted in SSA, played a vital role in the Green revolution (Evenson and Gollin, 2003, 758-759). Typically researchers develop a general innovation (such as fertiliser or different seed varieties) designed to increase productivity, after initial testing, the innovation is then be adapted to accommodate region specific factors, such as climate (Evenson and Gollin, 2003, 759). According to Evenson and Gollin (2003, 758), international programs attempted to bypass region specific testing. In SSA, modern variety (MV) seeds intended for Asia were distributed, providing a possible explanation for low adoption rates at the time.

This section has demonstrated that increases in agricultural production, driven by agricultural innovation, have been a successful tool for human development during the green revolution. However, low adoption rates of these technologies have impeded rural development in SSA. Moreover, the benefits of agricultural innovations are primarily felt by wealthier farmers. This investigation continues on the presumption that sustainable intensification, for those who experience it, addresses the issues raised by human development and the sustainable development approach. The links between participatory approaches and agricultural development are more thoroughly explored in section 4.

2.3 Farmer typologies

This investigation concentrates, as mentioned previously, more specifically on SSA. In order to improve living standards in the region, it will need to vastly increase its agricultural production (Dethier and Effenberger, 2012, 177). One recurrent theme voiced by many development organisations, including the African Development Bank, is that this increase must be sustainable (African Development Bank, 2012, 40; Lee, 2016, 1325). As a result, these institutions promote agricultural technologies that: use less off-farm products (such as purchased fertilisers, pesticides and machines); apply improved management techniques; mobilise locally available natural resources and purchased inputs in an efficient way (Lee, 2016, 1325). As was seen in the Green Revolution, the use of agricultural innovations for intensification is effective for those who have good access to the appropriate innovations. However, the provision of unsuitable innovations during the green revolution impeded their uptake in SSA. Today vast amounts of research have been carried out to develop more region specific innovations, yet adoption rates remain low (Brick and Visser, 2015, 383; Evenson and Gollin, 2003, 758-759).

This section demonstrates how different farm-typologies have been used to identify high adopting farmers. A review of the literature reveals that antecedent investigations have primarily focused on structural typologies, which provide a limited understanding of adoption rates. This review also discusses the recent idea of motivational typologies, which group smallholder farms based on their motivations and aspirations. Through a discussion of the potential benefits of motivational typologies, this investigation establishes that there is a need to empirically test their predictive capacity.

In the early 1980s, a debate started regarding adoption rates (Nowak, 1987, 202). Original theories stated that farmers needed greater access to agronomic and economic information (Nowak, 1987, 202). Nowak (1987, 202) argues that there is also a significant need to consider networks and the ways which farmers share information between one another. As well as this, farmers lack the short term financial incentives to adopt conservation technologies (Nowak, 1987, 202). To remedy these two problems, efforts should be made to integrate farmers into information and assistance networks (Nowak, 1987, 202).

Feder and Umali (1993, 235) discuss another factor that influences adoption rates. They identify how government policy and market conditions can have a significant effect on the likelihood of adoption. In short, farmers will not take on the risk of a new innovation if they have no assurance that they will receive a fair price for their produce. Inappropriate policy interventions can lead to severe misallocations of resources and capital, benefiting the wealthiest farmers. By comparing the Kenyan and Tanzanian coffee industry in the 1970s, it is possible to see that effective policy intervention in Kenya allowed for further research into new varieties, increased technical advice and marketing services (Bates, 2003, 43). Access to such information can help catalyse adoption, as outlined by Nowak (1987, 202). In contrast, the Tanzanian policy intervention gave little by way of advice, operated inefficiently and imposed non-competitive prices for coffee, stunting the growth of the agricultural sector (Bates, 2003, 43).

The ideas outlined by Bates (2003, 43) help to develop an understanding of the theoretical reasons for low adoption rates. However, the framework used by Bates (2003, 43) relies on the assumption that markets and governments most significantly influence adoption rates. Based on this perspective, increasing adoption rates would require significant changes in government policy. It has been found that the inertia associated with policy formation, particularly in sub-Saharan Africa, can be frustrating (Chanyalew, 2004, 41). As an alternative, some have tried to develop means of increasing adoption rates that bypass the need for such slow change. In order to understand these methods for increasing adoption rates, it is important to understand Biggs' (1990, 1482) framework for the diffusion of agricultural innovations. Biggs (1990, 1482) discusses the different stages, or linkages, through which agricultural innovations diffuse. Firstly innovations are developed in a network of international agricultural research centres. Following this, innovations are passed on to national agricultural research systems. National agricultural extension systems then distribute the innovations to early adopting farmers. If these innovations are properly implemented by early adopting farmers, who deem them to be useful, they are then passed on to late adopting farmers. From this framework it can be concluded that the initial distribution of agricultural innovations must be successful. If early adopting farmers do not fully commit to using the innovations, this decreases the chances that they will be effective. In turn, this minimises the possibility that early adopters will promote these innovations for late adopters, stunting horizontal diffusion. For this reason, it is essential that committed adopters are identified at the first stages of intervention as this will promote horizontal diffusion of the innovation and allow for greater impact.

Initially, to identify high adopting farmers, researchers focused on the relationship between farm structures and adoption rates (Baum, 1986, 290-291). For example, it was thought that farm size influenced adoption rates, leading development organisations to conclude that small farmers could not be targeted for new technologies (Baum, 1986, 290-291). Not only is this problematic, as it leaves smaller and less wealthy farmers behind, but it was later proved incorrect (Baum, 1986, 290-291). According to Baum (1986, 290-291) farm structure research continued, the findings of which suggested that resource endowment was the primary factor influencing adoption rates. For example, the quality of soil or irrigation could affect the likelihood that smallholders adopt a new technology. Until recently, attempts to characterise farmers were still dominated by structural typologies. An article published in 2013 provided a literature review of general farming typologies, all of which were associated with farm structure (Ma *et al.*, 2013). However, it has been recognised that assumptions based on structural typologies do not fully account for the heterogeneity of farms (van der Ploeg *et al.*, 2009, 124-125). Opposition to structural typologies continues today (Ploeg, 2018, 517).

One study found that agricultural development needed to take a more subjective approach to understanding the heterogeneity of farmers by gaining a deeper insight into the individual motivations of farmers (Methorst *et al.*, 2017, 16). This is confirmed by van der Ploeg who found that structural-typologies needed to be combined with an understanding of farmers' individual motivations. Recent research has tested the diversity of these motivations. Karali *et al.* (2014, 955) studied Swiss farmers and found that their eagerness to adopt new technologies was influenced by image, risk aversion, environmental attitudes and a range of other factors. Some may argue that a Swiss sample is not representative and hence is not useful for wider conclusions. However, the fact that motivational heterogeneity occurs on such a small scale (i.e. only between Swiss farmers) is suggestive of greater diversity at an international level. Meijer *et al.* (2014, 1) discuss that the oversight of farmers' individual motivations and aspirations has hindered the effectiveness of development strategies, particularly in relation to adoption rates. The authors state that adoption rates are influenced by three intrinsic factors: knowledge, perceptions and attitudes. Additionally, it is not stated that conventional methods of understanding adoption are incorrect. Instead, the authors state that there is an intermediate step, where farm-structure characteristics affect farmers' knowledge, perception and attitudes which in turn affect adoption rates (Meijer *et al.*, 2014, 12).

Meijer *et al*. (2014, 12) emphasised the need to empirically investigate the use of motivational typologies in conjunction with structural typologies. Hammond *et al.* (2017) carried out such research. Using principle component analysis (PCA) the authors found 6 farm-structure typologies and 6 motivational typologies. The motivational typologies were found within each structural typology showing that diverse motivations must be considered. The study revealed that a minority of the motivational typologies should be expected to adopt new technologies. The study carried out by Hammond *et al.* (2017) did not compare any of the typologies with actual adoption rates.

3. Research Question

This section outlines precisely what the case study aims to investigate. As previously discussed, increased agricultural production in SSA has the potential to sustainably catalyse human development by empowering smallholder farmers. Agricultural innovations are one of the most effective ways to achieve this, however, the rate at which they are adopted in SSA remains low. Moreover, agricultural interventions are largely adopted by wealthier smallholder farms, leaving the poorest farms behind. Development initiatives have attempted to target the farmers who are mostly to innovate by adopting these technologies, however, current targeting methods rely heavily on structural typologies. This investigation aims to find more effective means of predicting innovation in small farms. Building on the work of Hammond *et al.* (2017), the predictive power of motivational typologies is empirically tested against real-life adoption rates. This investigation seeks to identify a group of high adopting farmer, in the lowest wealth category, to ensure that the benefits of agricultural innovations can be felt by all. This is carried out using data from the first five years of the Africa RISING project initiated by USAID. Moreover, to truly test the effectiveness of motivational typologies, they are compared and combined with farm-structure typologies.

Can farmer typologies be used to predict adoption rates for the poorest farmers, and therefore, increase the impact of rural development programs on the rural poor?

4. Research Methodology

As stated in section 3, this investigation draws on data collected in relation to the USAID funded Africa RISING program. This section outlines exactly how this data is used to examine the relationship between farmer typology and predicted adoption rates. This outline is broken down into several components. Firstly, it is necessary to gain a deeper understanding of the aims and execution of the Africa RISING project, which demonstrates the connection between the theory outlined in section 2 and the real world application of agricultural development. Secondly, this section explores the survey carried out by ILRI, identifying the key parameters necessary to investigate adoption rates. Finally, this section outlines the key statistical techniques needed to conduct the analysis.

4.1 About "Africa RISING"

Africa RISING is a development program which aims to alleviate poverty and hunger for smallholder farmers using sustainably intensified farming system (International Livestock Research Institute, 2012, 5). Through an iterative process of research and development, Africa RISING aims to uncover more effective ways of using sustainable intensification technologies. Two broad research objectives and two development objectives are outlined by the initial project proposal (International Livestock Research Institute, 2012, 5).

Research Objectives:

1. "To identify and evaluate demand-driven options for sustainable intensification, that contribute to rural poverty alleviation, improved nutrition and equity and ecosystem stability".
2. "To evaluate, document and share experiences with approaches for delivering and integrating innovation for sustainable intensification in a way that will promote their uptake beyond the Africa RISING action research sites".

Development Objective:

1. "To create opportunities for smallholder farm households, within Africa RISING action research sites, to move out of poverty and improve their nutritional status – especially of young children and mothers – while maintaining or improving ecosystem stability".
2. "To facilitate partner-led dissemination of integrated innovations for sustainable intensification beyond the Africa RISING action research sites".

Research Objective 1 shows an awareness of the importance of adoption rates and a desire to find innovative ways of lowering the barriers to further adoption. Research Objective 2 and Development Objective 2 show the importance of the horizontal diffusion process outlined in section 2. Indicating that the Africa RISING program aims to have impacts beyond the beneficiaries it directly targets.

4.2 The Africa RISING Action Plan: How Agricultural Interventions were Distributed

The Africa RISING program can be subdivided into three projects located in: West Africa; Eastern and Southern Africa; the Ethiopian Highlands. This investigation examines data collected in the Ethiopian Highlands by the ILRI. The data was collected after “phase 1” of the program, which took place between 2012 and 2016. This subsection provides a summary of the project over this time period based on the biannual technical reports published by ILRI. This illustrates exactly how technologies were provided to households, which is a prerequisite for a deeper understanding of the adoption process. A great variety of initiatives were taken over this time period, therefore only those strictly relating to the adoption process are noted in this summary. Additionally, this investigation does not discuss the region specific particularities of the innovations distributed as it aims to provide a generalised insight into the adoption process which can be applied broadly to other regions.

To begin with, it was necessary for researchers to identify the most effective and applicable technologies to use for intervention. Beginning in April 2013, researchers began a Sustainable Livelihoods Asset Evaluation (SLATE) (Thorne, 2013, 2). Researchers conducted surveys, selecting households based on previous development operations conducted in the area (Thorne, 2013, 6). Thorne (2013, 7) reported that Woredas’ administration (the third level of administrative unit in Ethiopia), regional research teams and local University site teams also played a cooperative role in conducting the surveys. The surveys were conducted across 8 Kebeles (the smallest administrative unit in Ethiopia). This allowed researchers to identify structural typologies based on five types of livelihood asset: human, physical, social, natural and financial capital. The fact that structural typologies were already used is important to note, as it may affect the significance of the results of this investigation, this is discussed more thoroughly in section 6.

Researchers also undertook participatory community analyses (Thorne, 2013, 2). These involved community discussions in order to identify the barriers to increased agricultural production in each Kebele. From these discussions, the research teams determined the most applicable technologies to use for interventions. Researchers also used previously collected data to gain a deeper understanding of intensification barriers and to confirm the legitimacy of using the selected technologies (Thorne, 2013, 11). Participatory workshops were also held, allowing farmers to learn how to use new technologies, ensuring that knowledge was not a barrier to adoption, it was noted that these were appreciated by participants (Thorne, 2015, 7). The participatory community analyses and participatory workshops exemplify how the participatory approach to development is linked to agricultural development.

The active involvement of researchers and development professionals in the Africa RISING project created an environment of support and information sharing which is conducive to high adoption, as outlined in section 2. As the program was not deficient in these areas, it provided a useful a platform to analyse the use of typologies for predicting high adoption rates.

4.3 Data Analysis Techniques and RHoMIS Survey Data

This subsection describes how the post-intervention survey data, collected by ILRI, can be used to address the research question outlined in section 3. The research question can be broken down into several hypothesis:

H1. Structural typologies, which group farmers based on structural characteristics (such as farm size, livestock holdings and crop diversity) can be used to identify groups with significantly higher adoption rates.

H2. Motivational typologies, which group farmers based on their attitudes and motivations (such as willingness to change, plans to change their farm and plans to continue farming) can be used to identify groups with significantly higher adoption rates.

H3. Motivational and structural parameters can be combined in order to create another variety of typology, a combined typology, which can be used to identify groups with significantly higher adoption rates.

H4. Each set of typologies can be used to identify farmers in the lower wealth quartiles with significantly higher adoption rates.

Firstly, this subsection outlines the relevant parameters necessary to create the typologies, how these were selected and how these were recoded to facilitate further analysis. This section then examines the statistical techniques used to create the typologies, hereafter referred to as clusters. This subsection concludes by providing a brief explanation of how to quantify adoption and the relevant statistical techniques needed to investigate the hypotheses. In short, important variables were found using Principal Component Analysis (PCA). Following this, the desired components were used to generate a Gower Dissimilarity Matrix, which showed how different each household was from other households. Finally, Partitioning Around Medoids was used to group households into “Clusters” based on their degrees of similarity. The traits of these clusters were identified, making them into typologies.

The data analysed for this investigation was collected by ILRI, who led the USAID funded Africa RISING program in the Ethiopian Highlands. The Rural Household Multi Indicator Survey (RHoMIS) contains an extensive set of questions designed to give a detailed overview of on-farm activities whilst also providing some information about off-farm activities (Hammond, Fraval, *et al.*, 2017). All data analysis was carried out using R (R Core Team, 2013) and Rstudio software (RStudio Team, 2015). The following packages were used for the analysis: ggplot2 (Wickham, 2016a), plyr (Wickham, 2016b), dplyr (Wickham, François, Henry, and Müller, 2018), multcomp (Hothorn *et al.*, 2017), cluster (Maechler *et al.*, 2018), scales (Wickham, 2018), ade4 (Dray and Dufour, 2007).

As this investigation aims to take a more generalised approach, specific regional characteristic, such as crop and livestock varieties were avoided. Variables were selected using PCA. PCA is a useful technique for exploratory analysis (Joliffe, 2002, 111-149). It is primarily used to simplify data sets with large numbers of variables, identifying those which account for the most variation (Joliffe, 2002, 111-149). Using PCA, it was possible to determine the variables which accounted for the greatest differences between households. Additionally, PCA can be used in order to identify multiple variables which represent one another. For example, whilst carrying out PCA it became clear that the variables "Land Owned" and "Land Cultivated" were strongly correlated, meaning it was only necessary to use one of them.

4.3.1 Variables Associated with Structural Clustering

PCA can only be used on numeric data. However, it is also useful to understand the variation accounted for by ordinal variables (such as level of education). As a result, some variables were recoded, converted from ordinal to numeric, to accommodate PCA. Level of education (of the household head) was converted into a score between 0 and 1. 0 represented no education, 0.33 represented primary education, 0.67 represented secondary education and 1 represented further education. Additionally more descriptive indicators were also developed for the purposes of this PCA. To understand household typologies, it was necessary to understand how farmers directed their efforts. Household income is not a complete indication of farmer efforts as it does not take into account farm produce which is consumed. The RHoMIS survey data does, however, include data for "Value of Activities". This includes: value of crops consumed, value of livestock consumed, value of crops sold, value of livestock sold, off farm income. From this information it was possible to create numerous scales illustrating respondents' various types of productivity. The "total value of activities" (TVA) was calculated for each household. Using this variable, it was possible to determine the proportions of farmers activities dedicated towards cash crops, crops which were consumed and off-farm activities. The following four variables were created: Livestock orientation, proportion of TVA consumed, proportion of TVA which was sold, proportion of TVA which came from off-farm activities. These variables could be understood by their position on a scale from 0-1. With proportion of TVA consumed, a score of 0.6 would indicate that 60 percent of a respondents products are consumed at home. With livestock orientation, a score of 0.8 would indicate that 80 percent of the value of a respondents' on-farm activities are based around livestock.

4.3.2 Variables Associated with Motivational Clustering

For the creation of motivational typologies, it was also necessary to generate numerical variables from qualitative data. The RHoMIS survey asked respondents a range of questions relating to motivations, values and aspirations. For consistency in indicators, a 0-1 score was generated. A variable called the "innovation indicator" was designed based on the survey to indicate a farmers openness to change and new ideas. This was based on three value orientations. "How much effort do you personally put into achieving being curious and learning about new things?" "How much effort do you personally put into leading an exciting life?", "How much effort do you personally put into having new experiences and trying out new ways of doing things?". Value orientation questions in RHoMIS were designed on the basis that they are not region specific, and measure values that are present globally (de Groot and Steg, 2008; Hammond, van Wijk, et al., 2017; Stern, Dietz, and Guagnano, 1998). For each question, respondents could respond "no effort", "a little effort" and "a lot of effort". These were given the numerical scores of 0, 0.5 and 1 respectively. In addition, respondents were asked whether they would use any excess cash to invest in their farms. As this indicated a willingness to progress and innovate, farmers who responded "yes" were given a score of 1 and those who responded "no" were given a score of zero. Finally respondents were asked about their plans to change the following parameters: area of land, amount of crops, diversity of crops, amount of crop inputs (e.g. fertiliser), amount of livestock, diversity of livestock, amount of livestock inputs (e.g. feed), the amount of produce sold and their level of engagement in off-farm employment. If respondents indicated a desire to either increase or decrease any of these aspects of their life, one point was given. The total plans to change was equal to the sum of all nine components, this was then divided by 9 to achieve a 0-1 scale. The three components (value orientation questions, future investment, and plans to change) were given an equal weight and averaged in order to produce a final innovation score on a 0-1 scale. To measure a respondents commitment to agriculture, they were asked whether they wanted their children to continue farming. They were also asked whether their children themselves wanted to go into agriculture. Respondents who answered "yes" to one question were given a score of 0.5 and respondents who answered "yes" to both were given a score of 1. Finally, a third variable was created to demonstrate the direction in which farmers intended to change. For the "future plans" questions. Each response of "less" was assigned a numeric value of -1 while responses of "more" were given values of +1. The counts were once again tallied and averaged to generate a score on a 0-1 scale.

4.3.3 Variables Associated with Combined Clustering

For the combined motivational and structural typologies, the most descriptive variables for households were simply a combination of the variables from both the motivational and structural typologies. However, after conducting a PCA, it became clear that the "commitment to agriculture" score was responsible for little variation across households within this set of variables and was consequently dropped.

4.3.4 Making Typologies Out of Variables and Testing Whether their Differences are Significant

Following the identification of these variables, it was necessary to make the typologies. Firstly each set of variables was arranged in a Gower dissimilarity matrix. This is a statistical technique which effectively measures how different each household is from other households (Gower, 1971, 857-871). Another technique, Partitioning Around Medoids (PAM) clustering was then used to group households based on their similarities (Kaufman and Rousseeuw, 1990). It was important that the clusters selected actually represented important variations in the data. To ensure this, the appropriate number of clusters had to be selected, this was done using a test of silhouette width (Rousseeuw, 1987). This graphical test illustrates the variance in the data which is accounted for by selecting a particular number of clusters. To select the most representative clusters, one must simply select the number with the greatest silhouette width. Finally, the Tukey Honest Significant Difference (HSD) test, related to the Analysis of Variance (ANOVA) test, was used to test the variation between clusters and whether it is significant (Jaccard, Becker, and Wood, 1984, 589-596). From hereafter, significance refers to the statistical norm of 95 percent (Goodman and Berlin, 1994). If a result was classed as significant, there is only a 5 percent chance that it could have occurred by random chance (Goodman and Berlin, 1994). The appropriate significance tests were used to test hypotheses H1, H2, H3 and H4. When investigating the relationship between two nominal variables, Chi-Square tests were used as was appropriate (McHugh, 2013).

4.3.5 How to Measure Adoption

Finally, once the clusters had been created, it was necessary to test whether they accurately predict adoption rates. The RHoMIS survey, tailored to the Africa RISING project, asks questions relating to the interventions offered by Africa RISING. Firstly respondents were asked which innovations they have tried since the project began in 2012. They were then asked which ones they have continued, or plan to continue, using since phase 1 of the project ended. Finally, respondents were asked to what extent they intended to use the each of their innovations. Here they could respond "less", "same", "more" or "much more". To calculate the adoption rate, the number of innovations they continued to use was divided by the number of technologies they tried, indicating the percentage of innovations which respondents had continued using. In order to calculate adoption strength, the responses "less", "same", "more" and "much more" were given the scores -1, 0, 0.5 and 1 respectively. The weightings were applied to the answers, added, then divided by the total number of responses given, giving adoption strength. After this had been calculated for each household, it was possible to compare adoption rates and adoption strength for various subsets.

4.3.6 Grouping Farmers Based on Wealth

After clusters had been created, to address H4 it was necessary to divide the population based on wealth in order to see whether groups of high adopting farmers could be found in the lowest wealth quartiles. As stated in section 4.3.1, the RHoMIS survey includes the "value of activities" for the various undertakings of each household. It was important to consider the TVA of each household, rather than income, to account for the heterogeneity of smallholder farms. According to previous work with the RHoMIS application, by calculating the TVA of each household, it is possible to divide them into Food Availability (FA) quartiles (Hammond, Fraval, et al., 2017, 226). This effectively measures their wealth by the caloric purchasing power of their activities. Finally, the Tukey HSD test was used to test the significant difference in adoption rate, as well as adoption strength, for clusters in each FA quartile.

5. Results

This section outlines the results of the approaches specified in section 4. Before presenting the results obtained when testing the core hypotheses used for this investigation, it provides an overview of the data in subsection 5.1. In the main body of the results, which are summed up in subsections 5.2, 5.3 and 5.4, each type of clusters is examined one after the other: first the structural clusters, then the motivational cluster, and finally the combined clusters. For each of these clusters, a systematic approach is applied. First, the noteworthy attributes of the "average farmer" deducted from the data set are described. Then the results of the Principle Component Analysis (PCA) are indicated, revealing which variables were most representative of the differences between households. As explained in section 4.3.4, the results of this PCA were used to create clusters. So for each type of cluster studied in the present section, the results of the Partitioning Around Medoids (PAM) clustering are displayed, outlining exactly how each cluster can be qualitatively described. The adoption rates are given, as well as the number of respondents, and at the end of the presentation of the results for each type of clusters, two questions are asked: can the adoption rates be predicted for the whole population of farmers and can they be predicted for the lower quartile.

The various adoption rates corresponding to the three types of clusters (structural, motivational and combined) are compared and summarised in subsection 5.5. For this comparison, first the population is taken as a whole, to see whether adoption rates vary significantly between each cluster. Then the population is divided into wealth quartiles, to see whether each type of cluster can predict high adoption rates in the lower wealth quartiles. Finally, the reasons for which farmers adopted innovations, as well as the reasons preventing further adoption, are outlined in subsection 5.6. An extensive analysis was carried out in relation to adoption rates, which could not be included in detail in this section. To avoid repetition, and present only the most relevant findings, all results in this section pertaining to differences in adoption between clusters are statistically significant, according to the relevant statistical test. The absence of statistical significance is also important to note, the corresponding implications of this are discussed in section 6. Moreover, an explicit description of what was found, the meaning of these findings, in relation to development practice and development theory can be found in section 6.

5.1 An Overview of the Data Set: Describing the Average Household

It is important to have an initial understanding of the typical household, particularly as the results outlined here are relative. They only provide a complete picture when farmers are compared to one another. The data used in clustering, made up of responses from 779 smallholder farmers, was highly variable with significant outliers. As a result, medians have been used to provide a summary of the data. Households cultivated a median of 1.25ha of land. The median total income per year was $366. Both variables had a standard deviation similar to that of the median, indicating that they varied greatly. The median crop diversity was 7, while the median livestock diversity was only 2. Among the respondents, 20 percent had no formal education, 50 percent had been educated to a primary school level, 18 percent had received secondary education and 12 percent had benefited from some form of higher education. The median off-farm income was \$0, as only 32 percent of respondents reported having sources of off-farm income. The median farm income lay at \$201.161, with median crop sales at \$140 and median livestock sales at \$0, as only 44 percent of respondents reported selling any livestock. Households on average had a 10 percent chance of progressing out of poverty according to the standardised index designed to measure this possibility (Schreiner, 2016). For this investigation, poverty has been defined by the international US\$1.90 PPP line. With regards to adoption, 92 percent of respondents had tried at least one innovation. Importantly, respondents already had a mean adoption rate of 88 percent. Among the respondents, 48 percent stated that they were not receiving enough support to adopt more innovations, 42 percent that they had insufficient land to adopt more innovations and 25 percent that they did not have enough money to adopt more innovations.

5.2 Examining Structural Clusters

This subsection examines the structural clusters which have been developed using the techniques outlined in section 4.3.1 and 4.3.4. The results of the PCA reveal which variables were selected to generate structural clusters. The differences in adoption traits of the structural clusters were investigated, with the population as a whole. In addition, these differences between clusters were tested for each individual FA quartile. This revealed that there is insufficient evidence to support the use of structural typologies as a means to predict high adoption for lower FA quartiles.

5.2.1 Outcome of PCA: Which Variables were Most Representative of Differences in the Data

After conducting a PCA, the following variables were selected to create structural typologies:

- The education level of the household head
- The land cultivated
- Crop diversity
- Livestock diversity
- Livestock orientation
- The proportion of TVA which was consumed
- The proportion of TVA which was sold
- The proportion of TVA which came from off-farm activities

5.2.2 The Results of PAM Clustering: A Qualitative Description of Each Cluster

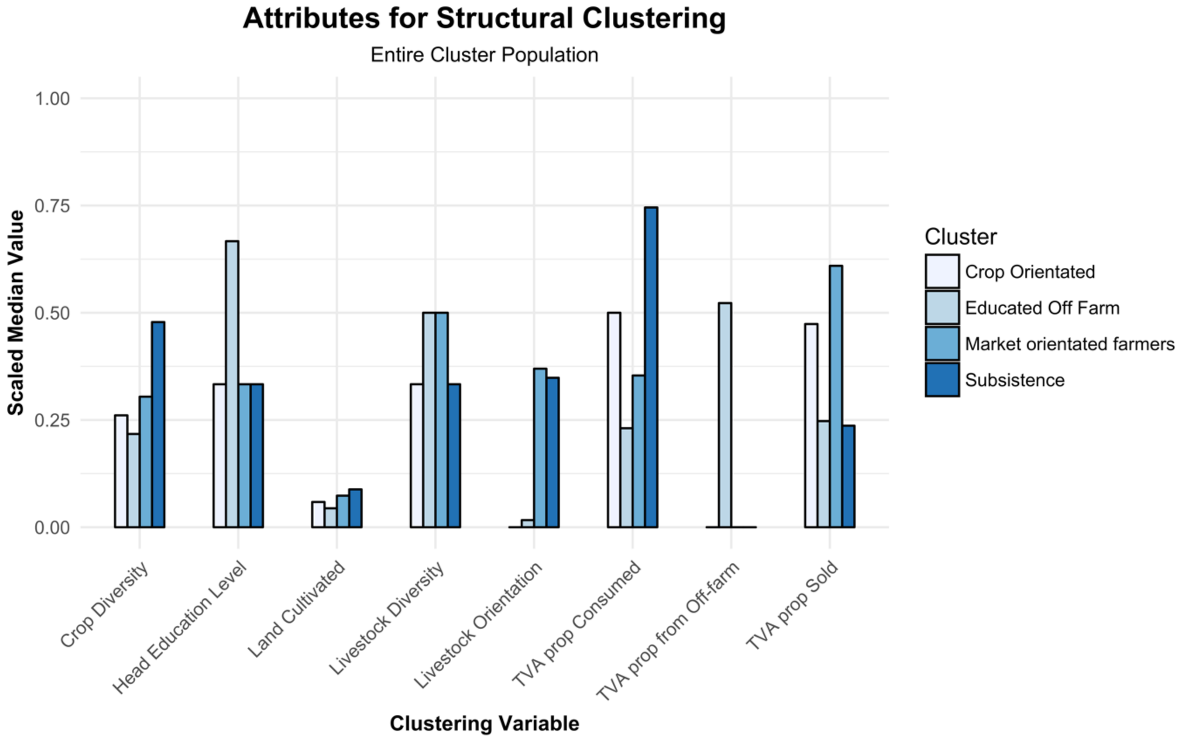

Figure 1. A visual representation of structural cluster composition. The x-axis displays the variables which were used to cluster households. The variables "Crop Diversity", "Land Cultivated" and "Livestock Diversity" were scaled to a 0-1 scale for the purposes of visual representation. All other variables remain unchanged. Based on data provided by the International Livestock Research Institute.

Using the variables selected through PCA, it was possible to create structural typologies with the PAM method. Figure 1 is a visual representation of how households were clustered based on structural characteristics, table 1 contains a qualitative description of this clustering and a quantitative description can be found in the appendix (appendix 1). Figure 2 indicates the number of respondents in each cluster.

The clusters were named based on their most notable features. From figure 1 and table 1 it can be seen that "market-orientated farmers" gained their name because of the proportion of their TVA derived from sold crops. This cluster, or typology, also displays higher livestock diversity. Additionally, these farmers place more focus on livestock production than any of the other clusters. "Educated off-farm" farmers were given this name because of their off-farm income, half of their TVA being derived from off-farm sources, and because they were the most educated of the clusters. For "subsistence" farmers, approximately three quarters of their TVA originated from products which were consumed. These farmers also cultivated the largest proportion of land and grew the most diverse set of crops. "Crop-orientated" farmers scored zero on livestock orientation and sold large proportions of their products but showed few other distinct features.

Cluster Name	Head Education Level	Land Cultivated	Crop Diversity	Livestock Diversity
Market orientated	Primary	Upper middle area	Middle	Higher
Educated off-farm	Secondary	Lowest area	lowest	Higher
Subsistence	Primary	Highest area	Highest	Lower
Crop Orientated	Primary	Lower middle area	Lower middle	Lower

Cluster Name	Livestock Orientation	TVA Proportion Consumed	TVA Proportion Sold	TVA Proportion Off-Farm
Market orientated	Higher	One third consumed	Majority sold	No off-farm income
Educated off-farm	Low	One quarter consumed	One quarter sold	Half of income from off-farm
Subsistence	Higher	Three quarters consumed	One quarter sold	No off-farm income
Crop Orientated	None	Half consumed	Half sold	No off-farm income

Table 1. A table qualitatively describing characteristics of structural clusters. A quantitative version of this table can be found in the appendix (appendix 1). The cluster names in this table are based derived on noteworthy characteristics. Based on data provided by the International Livestock Research Institute.

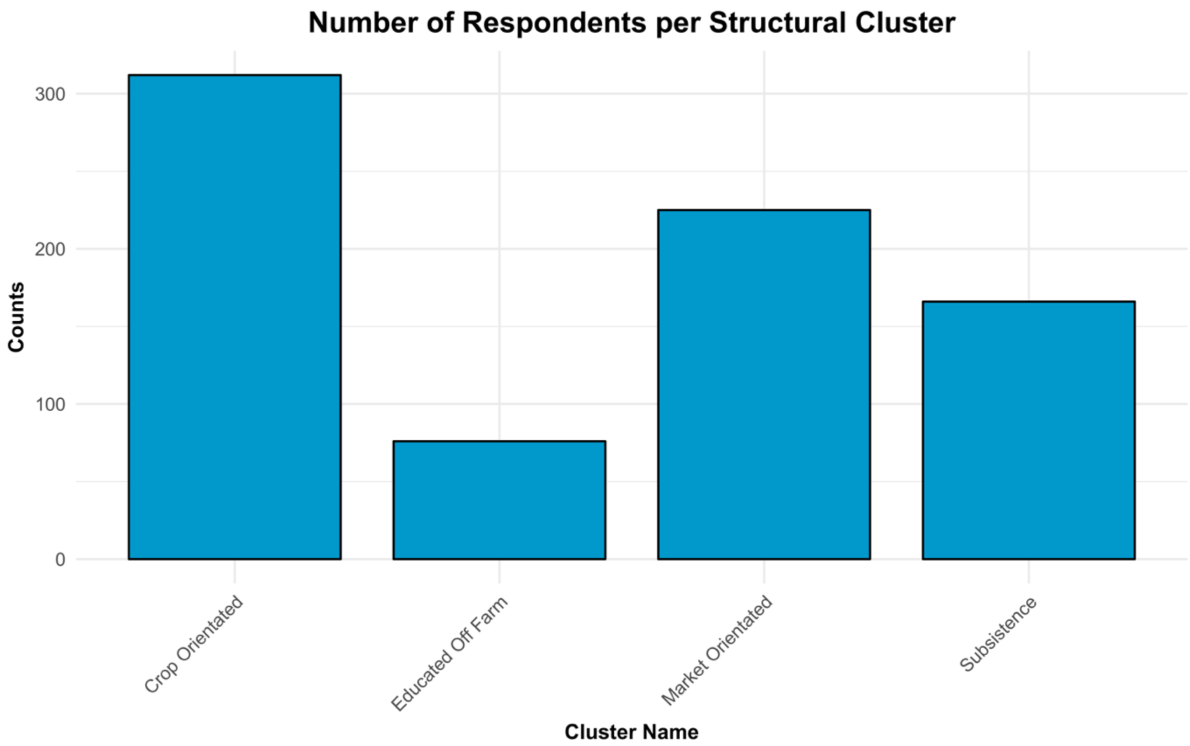

Figure 2. A bar-plot representing the number of respondents within each structural cluster. Based on data from the International Livestock Research Institute.

5.2.3 Can Structural Clusters Predict High Adoption for the Population as a Whole?

After having grouped farmers based on their similarities, through PAM clustering, it was then possible to compare the extent to which these groups adopted new innovations. Both adoption strength and adoption rate, as defined in section 4.3.5, were investigated.

Figure 3 illustrates the differences in adoption rate between structural clusters. Crop-orientated farmers had the highest adoption rate, at 91 percent. Market-orientated farmers and subsistence farmers had similar scores, at 88 percent and 87 percent respectively. Educated off-farm respondents had the lowest adoption rate at 81 percent.

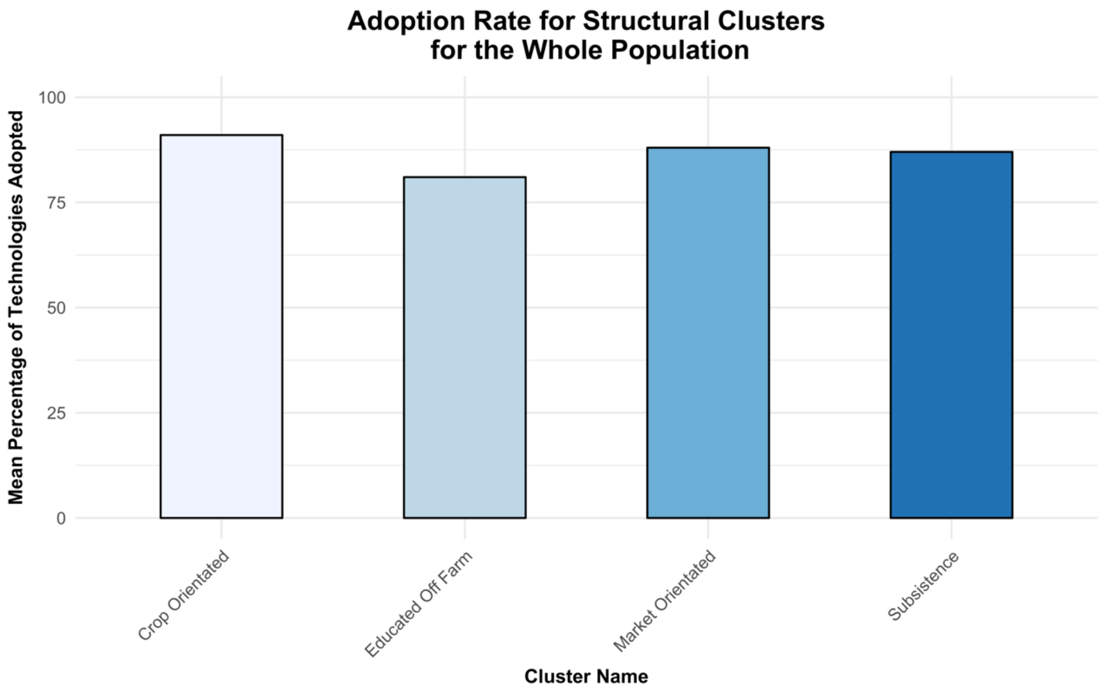

Figure 3. The mean adoption rate of each structural cluster when the survey population is taken as a whole. Based on data from the International Livestock Research Institute.

Figure 4 compares the adoption strength score of each structural cluster. In this instance market-orientated farmers achieved the highest average score, at 0.63. While crop-orientated, educated off-farm and subsistence farmers achieved scores of 0.61, 0.55 and 0.51 respectively. Meaning while market orientated farmers only had a medium adoption rate, they had a higher level of commitment to the technologies they did adopt. For subsistence farmers, the reverse is the case, they had a similar initial adoption rate but showed significantly less commitment.

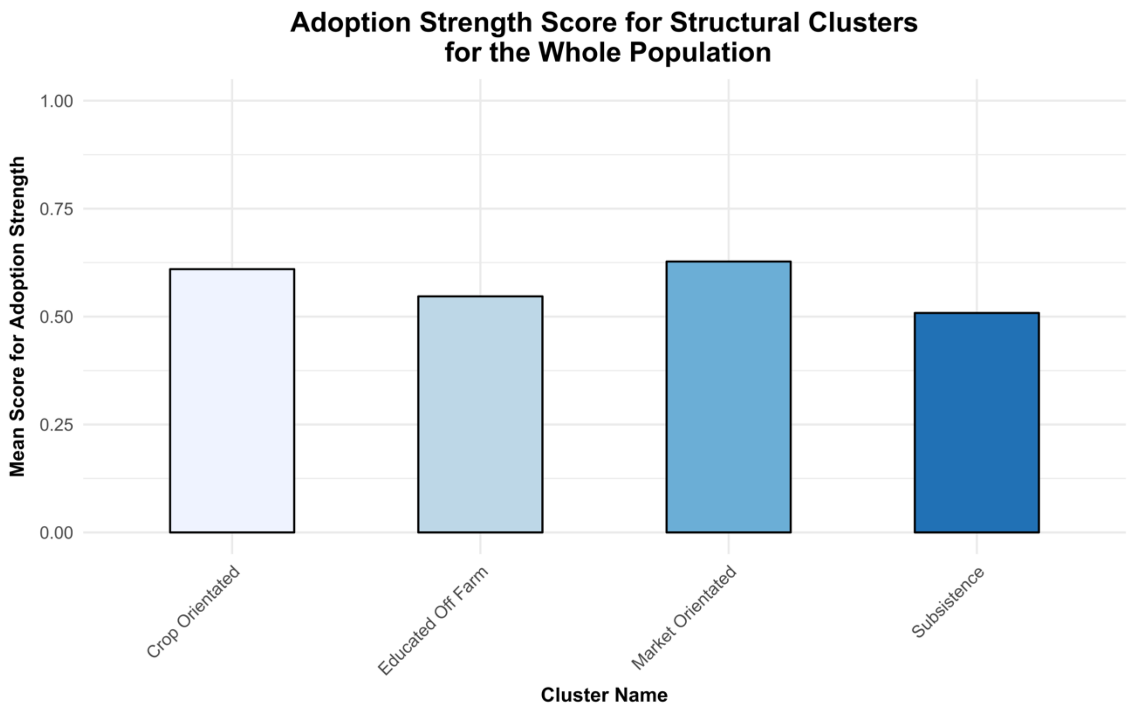

Figure 4. The mean adoption strength score of each structural cluster when the survey population is taken as a whole. Based on data from the International Livestock Research Institute.

To conclude this subsection. It was shown that structural clusters could effectively predict adoption rates and adoption strength when the population was taken as a whole. Proving hypothesis H1, for adoption rate, crop-orientated farmers had the highest score. For adoption strength, market-orientated farmers had the highest score.

5.2.4 Can Structural Clusters Predict High Adoption in the Lower Wealth Categories?

Section 5.2.3 illustrated how structural clusters can predict adoption rates and adoption strength when examining the whole population. To see whether structural clusters could be used to identify a group of high adopting farmers, in the lower wealth quartiles, the population was divided into FA quartiles. The findings of this process are illustrated in figure 5. It was found that there were only significant differences in adoption rate for the upper FA quartile. In this case crop orientated farmers had the highest adoption rate, at 90 percent. There was no significant relationship between the adoption rates of each cluster for the other FA quartiles. Moreover, there was no significant relationship between the adoption strength scores of each cluster for any of the individual FA quartiles.

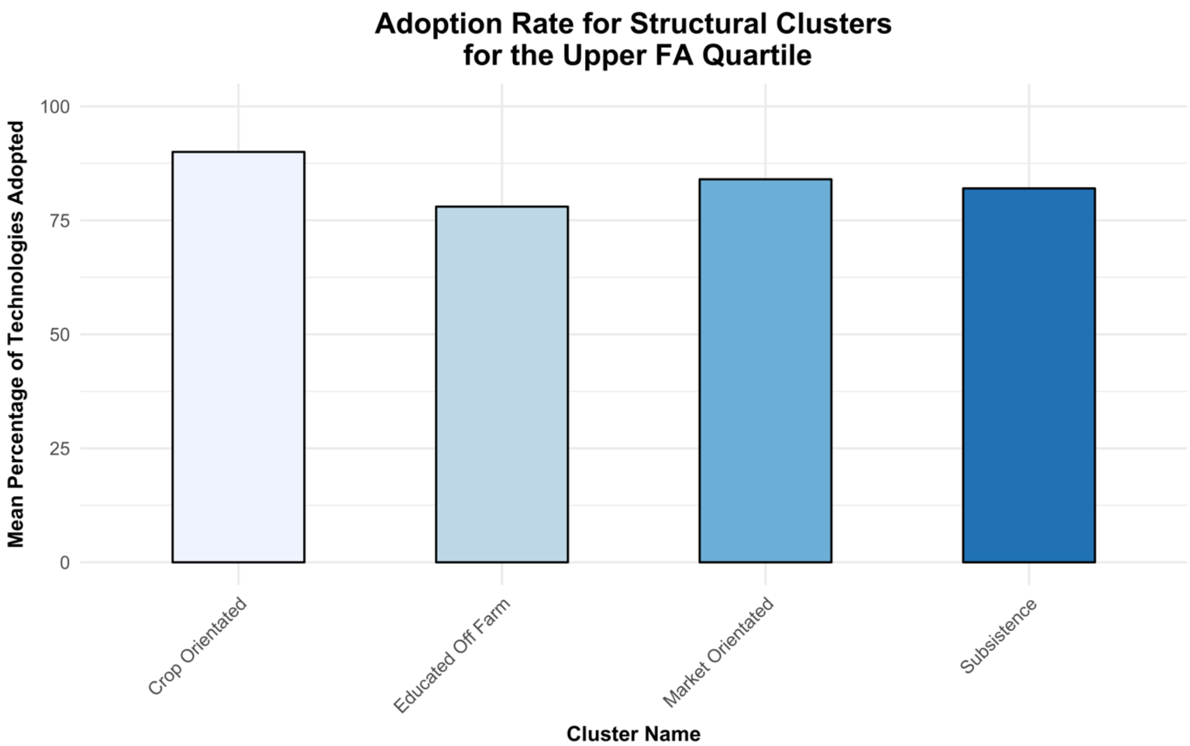

Figure 5. The mean adoption rate of each structural cluster when examining the upper FA quartile. Based on data from the International Livestock Research Institute.

5.3 Examining Motivational Clusters

This subsection examines the motivational clusters which have been developed using the techniques outlined in section 4.3.1 and 4.3.4. The results of PCA reveal which variables were selected to generate motivational clusters. The differences in the adoption traits of the motivational clusters are investigated in this section, with the population as a whole. In addition, these differences between clusters are examined for each individual FA quartile. This reveals that there is sufficient evidence to consider the use of motivational clusters to predict how strongly farmers commit to the innovations they adopt.

5.3.1 Outcome of PCA: Which Variables were Most Representative of Differences in the Data

For motivational typologies, the PCA revealed that all three indicators designed were responsible for significant amounts of variation:

- Their score on the innovation indicator
- Their score for commitment to agriculture
- The direction of their future plans, whether to increase their amount of activities, decrease their amount of activities or remain the same.

5.3.2 The Results of PAM Clustering: A Qualitative Description of Each Cluster

Using the results of the PCA, it was possible to apply the PAM method to the selected variables to create motivational clusters. Figure 6 provides a visual representation of motivational cluster composition, table 2 provides a qualitative explanation and a quantitative description can be found in the appendix (appendix 2).

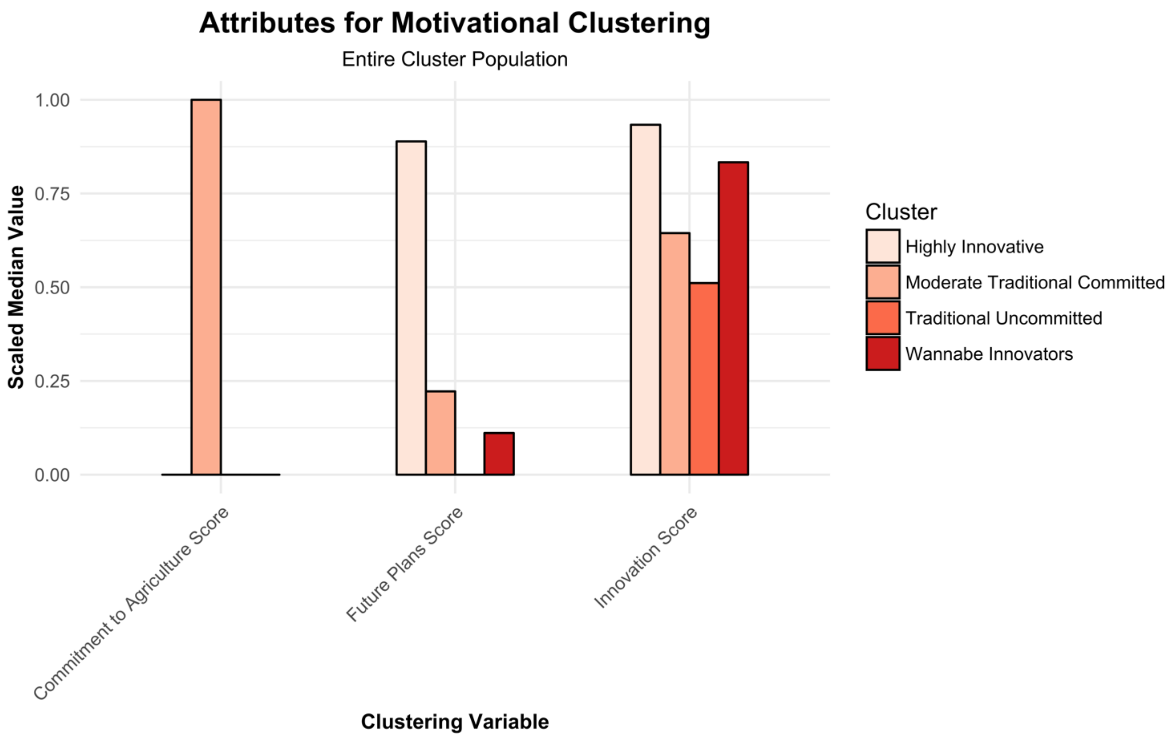

Figure 6. A visual representation of motivational cluster composition. The x-axis displays the variables which were used to cluster households. The variables were derived using the methods outlined in section 4.3. Based on data provided by the International Livestock Research Institute.

“Traditional uncommitted” farmers gained this title as they had no plan to increase future activities whilst also achieving a low innovation score. “Highly innovative” farmers scored highly in innovation whilst also showing a strong eagerness to increase their activities. “Wannabe innovators” were given this title as they scored similarly on innovation but showed much less of a desire to increase their activities. “Moderate Traditional Committed” was the only cluster with a non-zero commitment to agriculture score. This cluster had the second lowest score on innovation and future plans, hence the label of “Moderate Traditional.

Cluster Name	Commitment to Agriculture Score	Future Plans Score	Innovation Score
Traditional Uncommitted	Not Committed	No plans to increase activity	Lowest
Wannabe Innovators	Not Committed	Low plans to increase activity	Upper middle
Highly Innovative	Not Committed	Strong plans to increase activity	Highest
Moderate Traditional Committed	Committed	Lower-middle plans to increase activity	Lower Middle

Table 2. A table qualitatively explaining motivational clusters. Based on data provided by the International Livestock Research Institute.

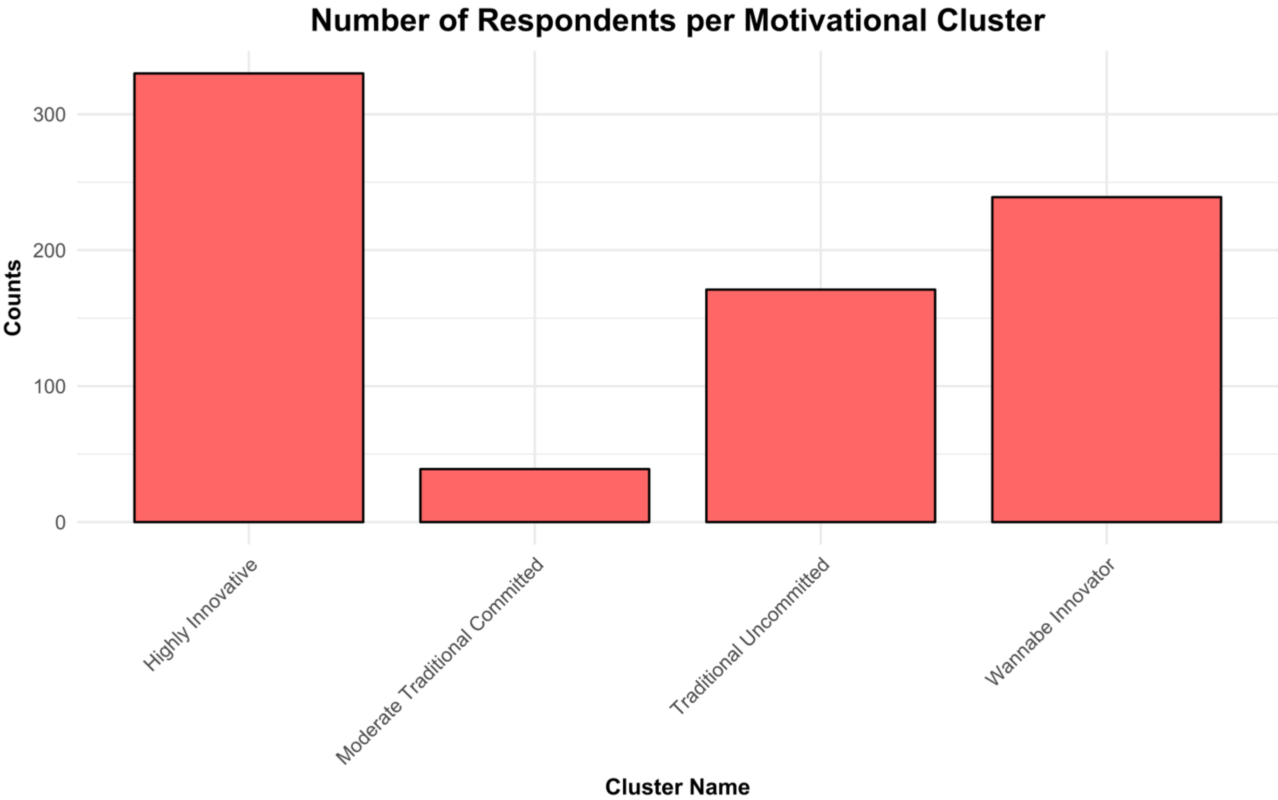

Figure 7. A bar-plot representing the number of respondents in each motivational cluster. Based on data provided by the International Livestock Research Institute.

5.3.3 Can Motivational Clusters Predict High Adoption for Population as a Whole?

After having grouped farmers based on motivational characteristics, it was possible to examine the extent to which these groups were open to new innovations. Both adoption strength and adoption rate, as defined in section 4.3.5, were investigated.

Figure 8 is a visual representation of the differences in adoption rate for each motivational cluster. Wannabe innovators had the highest adoption rate, at 92 percent. This was followed by highly innovative farmers, who had an adoption rate of 87 percent. Moderate traditional committed and traditional uncommitted had adoption rates of 83 and 86 percent respectively.

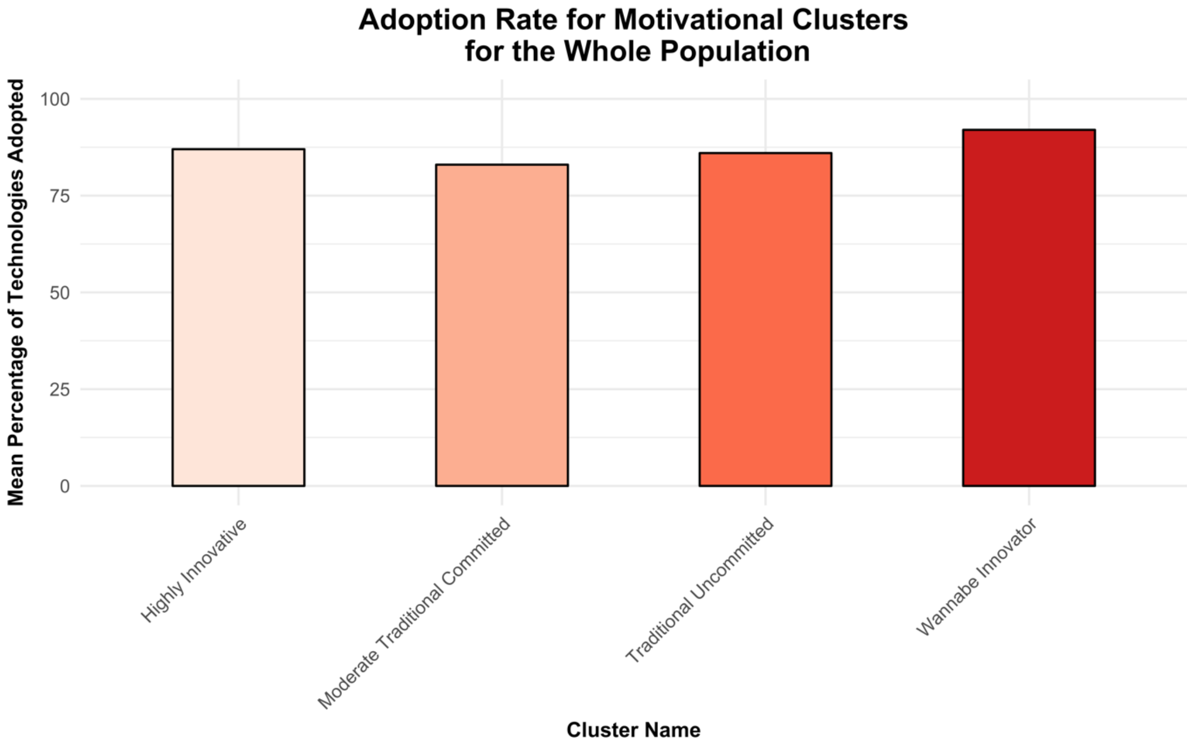

Figure 8. The mean adoption rate of each motivational cluster when the survey population is taken as a whole. Based on data from the International Livestock Research Institute.

Figure 9 illustrates how highly innovative farmers have a much higher adoption strength score, at 0.7, than the other motivational clusters. Wannabe innovator, moderate traditional committed and traditional uncommitted farmers had adoption strength scores of 0.52, 0.43 and 0.46 respectively. The ordering of these scores is supported by the idea that there is a strong correlation between innovation score and adoption strength.

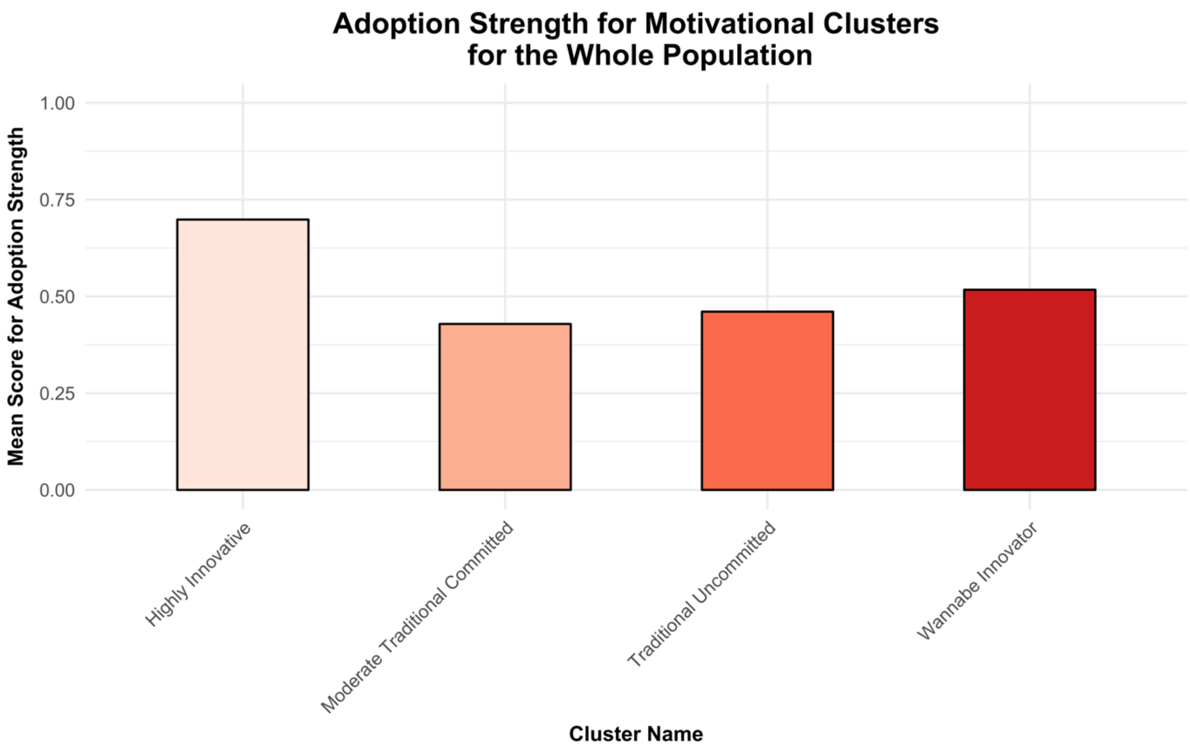

Figure 9. The mean adoption strength of each structural cluster when the survey population is taken as a whole. Based on data from the International Livestock Research Institute.

To conclude this subsection. The data showed that motivational clusters can predict high adoption rates and high adoption strength when the population is taken as a whole, proving hypothesis H2. For adoption rate, wannabe innovators had the highest score. For adoption strength, highly innovative farmers had the highest adoption rate.

5.3.4 Can Motivational Clusters Predict High Adoption in the Lower Wealth Categories?

Section 5.3.3 illustrated how motivational clusters can predict adoption rates and adoption strength when examining the whole population. To see whether motivational clusters could be used to identify a group of high adopting farmers, in the lowest wealth quartiles, the population was divided into FA quartiles.

For all of the individual wealth quartiles, there were no significant differences between adoption rates for the various clusters. However, for all individual wealth quartiles, there were significant differences between the adoption strength scores of each cluster.

Figure 10 shows the differences in the adoption strength score of motivational clusters, only looking at the lower FA quartile. Highly innovative farmers had the highest adoption strength score of 0.63. While wannabe innovator, traditional uncommitted and moderate traditional committed farmers had adoption strength scores of 0.41, 0.41 and 0.03 respectively.

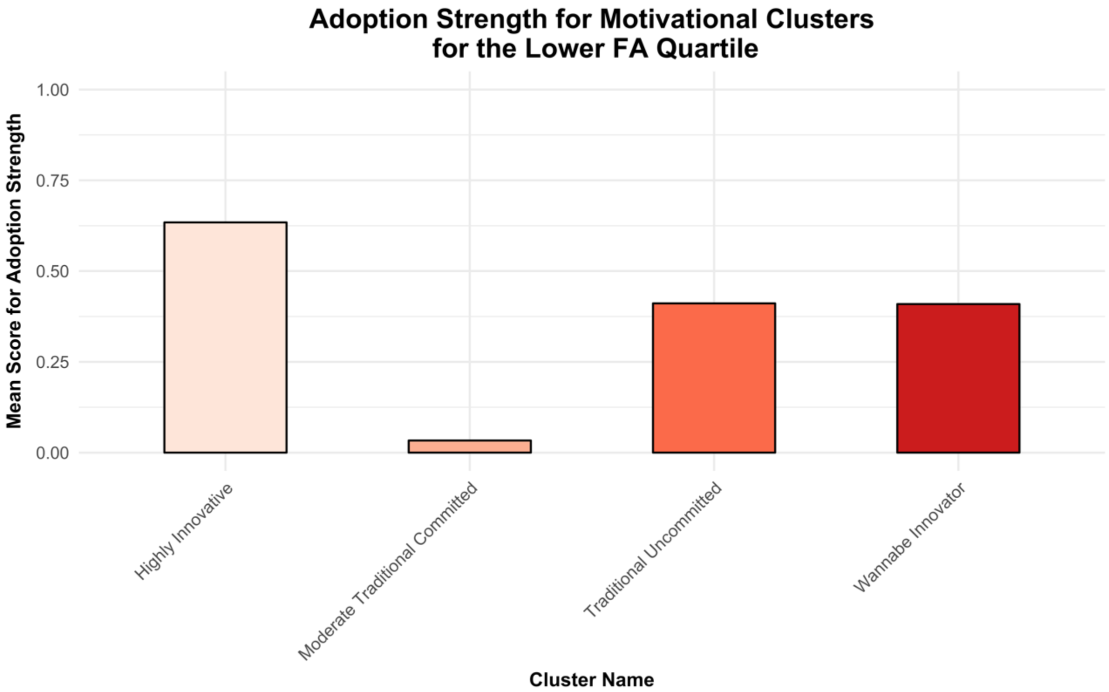

Figure 10. The mean adoption strength of each structural cluster when the examining the lower FA quartile. Based on data from the International Livestock Research Institute.

Figures 11, 12 and 13 show the adoption strength scores of motivational clusters for the lower-middle, upper-middle and upper FA quartiles respectively. In all three cases, highly innovative farmers had the highest adoption rate. Differences can be seen in the adoption strengths of wannabe innovator and traditional uncommitted farmers, however, these differences are only slight. The adoption strength for moderate traditional committed farmers is much lower for the lower FA quartile, compared to the other FA quartiles, the reasons for this are discussed in section 6.

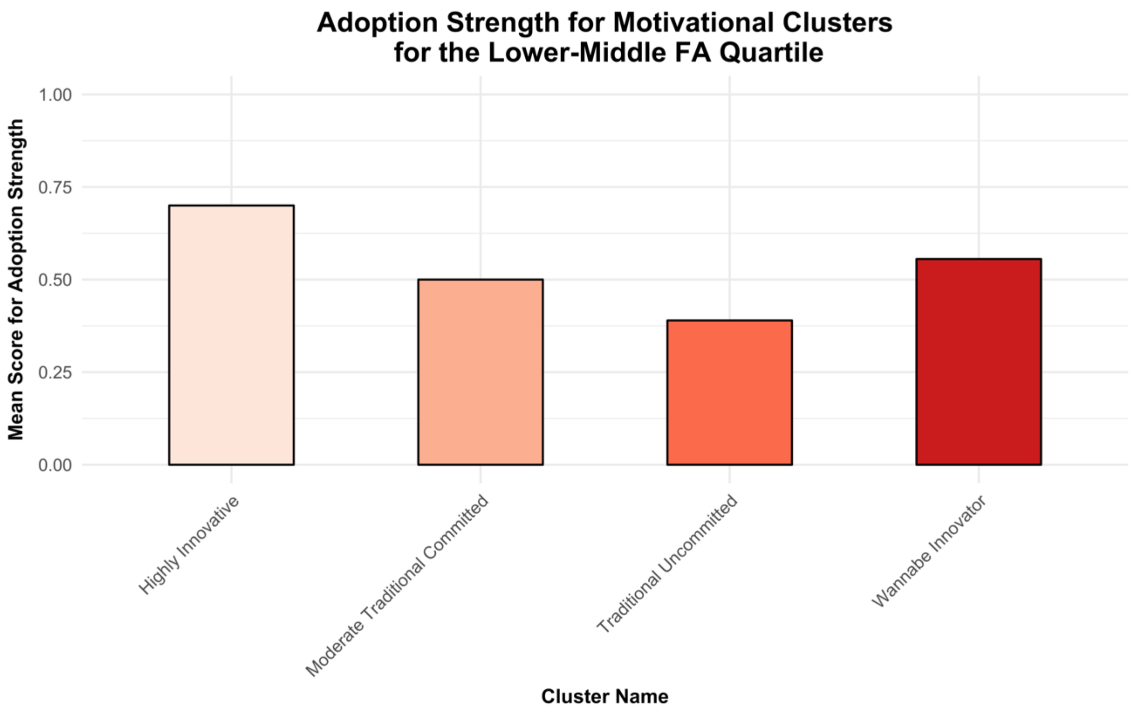

Figure 11. The mean adoption strength of each structural cluster when the examining the lower-middle FA quartile. Based on data from the International Livestock Research Institute..

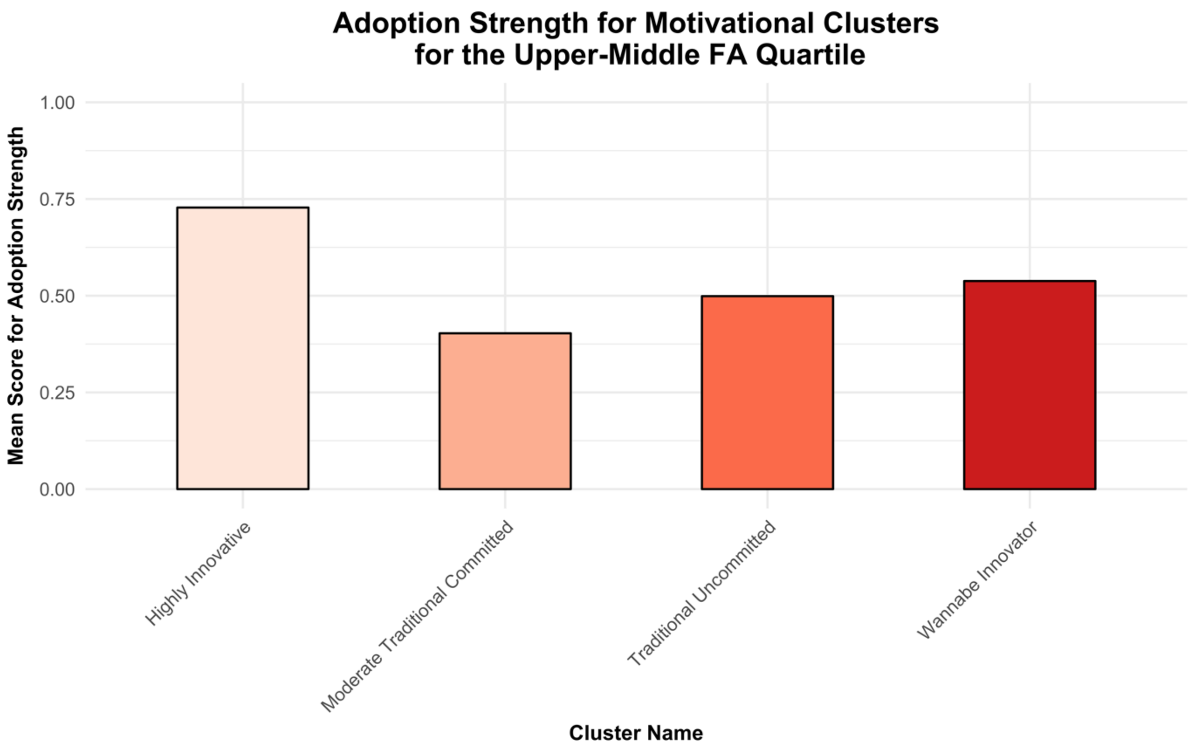

Figure 12. The mean adoption strength of each structural cluster when the examining the upper-middle FA quartile. Based on data from the International Livestock Research Institute.

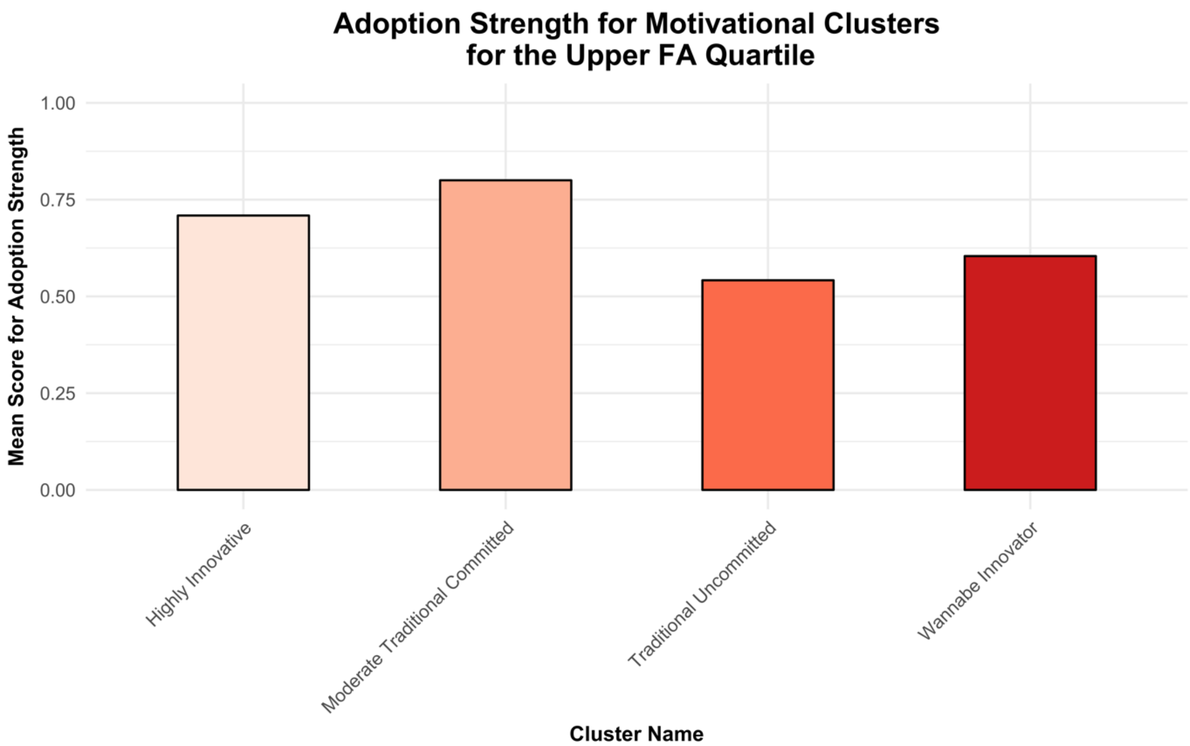

Figure 13. The mean adoption strength of each structural cluster when the examining the upper FA quartile. Based on data from the International Livestock Research Institute.

To conclude this subsection, there was insufficient evidence to suggest that motivational cluster could be used in order to predict higher adoption rates for the lower wealth quartile, a key component of the research question outlined in section 3. However, motivational clusters could effectively predict high adoption strength for the lower wealth quartiles. The implications of this are discussed in section 6.

5.4 Examining Combined Clusters

This subsection examines the combined clusters which have been developed using the techniques outlined in section 4.3.1 and 4.3.4. The results of PCA reveal which variables are selected to generate combined clusters. The differences in adoption traits of the combined clusters are investigated, with the population as a whole. In addition, these differences between clusters are tested for each individual FA quartile. This reveals that there is sufficient evidence to consider the use of combined clusters to predict adoption rates as well as predicting how strongly farmers commit to the innovations they adopt.

5.4.1 Outcome of PCA: Which Variables were Most Representative of Differences in the Data

PCA was applied to all the variables initially used to generate both the structural and motivational clusters. This revealed that the "commitment to agriculture" score was responsible for little variation across households within this set of variables and was consequently dropped.

The following variables were used to create a combined clusters:

- Education level of the household head
- Land cultivated
- Crop diversity
- Livestock diversity
- Livestock orientation
- The proportion of TVA which was consumed
- The proportion of TVA which was sold
- The proportion of TVA which came from off-farm activities
- The future plans score and the innovation score.

5.4.2 The Results of PAM Clustering: A Qualitative Description of Each Cluster

Four clusters were created using the combined variables. Figure 14 is a visual representation of these clusters, Table 3 provides a qualitative description. A numerical description of these clusters can be found in the appendix (appendix 3). The number of respondents in each cluster is visualised in figure 15. "Innovative cash croppers" sold more than half of their produce and had the highest score for the innovation indicator. They had a high livestock diversity and a relatively high livestock orientation. Additionally, "Innovative Cash Croppers" had the strongest desire to increase their amount of activities. "Innovative multitaskers" are defined by their greater engagement in off-farm activities, higher level of education, high innovation score and medium drive to increase activities. "Traditional subsistence" farmers are characterised by a large portion of TVA consumed, low innovation score, high crop diversity, high livestock orientation, low future plans score. "Traditional cash croppers" are also characterised by a relatively low innovation score, a high proportion of TVA coming from sold crops, lower level of education, a weak desire to change and a high level of crop orientation.

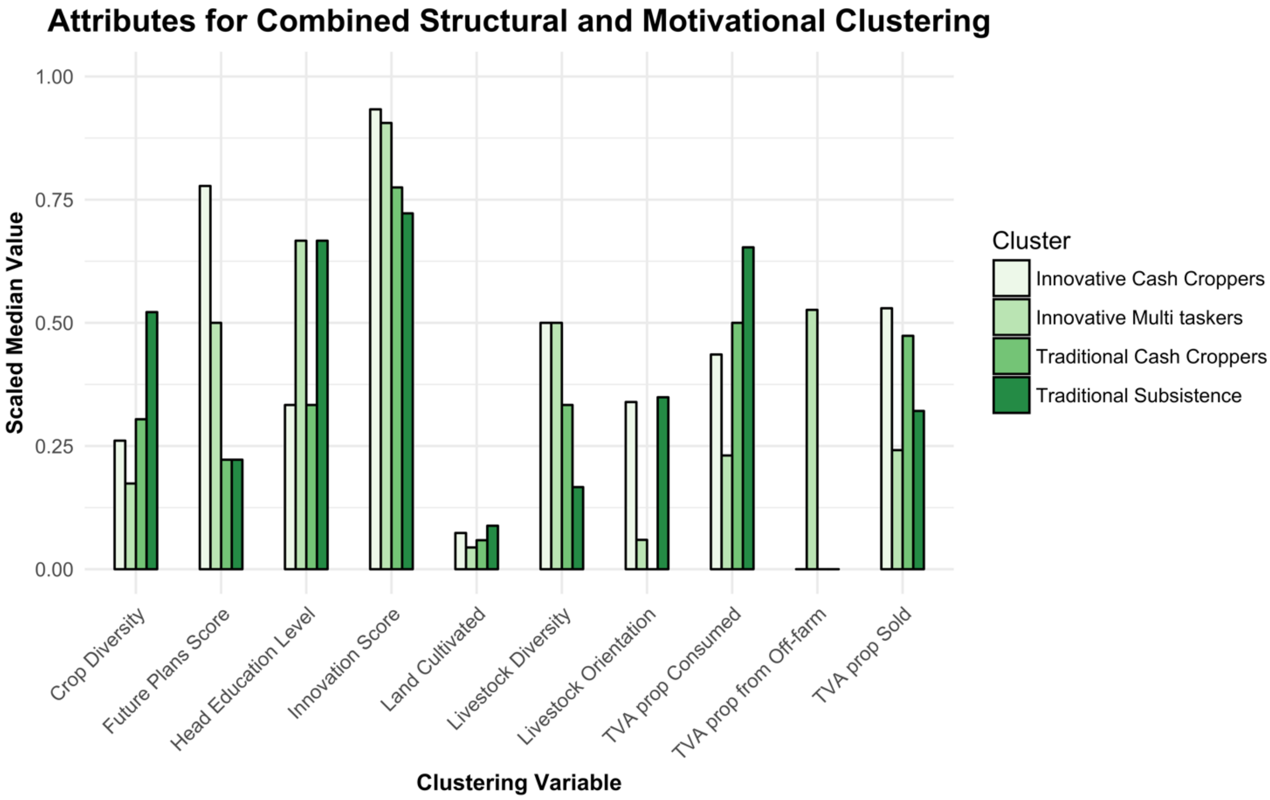

Figure 14. A visual representation of the combined cluster composition. Similarly to figure 1, "Land Cultivated", "Crop Diversity" and "Livestock Diversity" have been scaled for the purposes of graphical representation. Based on data provided by the International Livestock Research Institute.

Cluster Name	Head Education Level	Land Cultivated	Livestock Diversity	Crop Diversity
Innovative Cash Croppers	Primary	Upper middle area	Higher	Middle
Innovative Multi taskers	Secondary	Lowest area	Higher	Lowest Diversity
Traditional Subsistence	Secondary	Highest area	Low	Highest Diversity
Traditional Cash Croppers	Primary	Lower middle area	Middle	Middle

Cluster Name	Livestock Orientation	TVA Proportion Consumed	TVA Proportion Sold
Innovative Cash Croppers	High Livestock Orientation	Consume slightly less than half	Sell just over half
Innovative Multi taskers	More Crop Orientated	Consume a quarter	Sell one quarter
Traditional Subsistence	High Livestock Orientation	Consume majority	Sell one third
Traditional Cash Croppers	Strongly Crop Orientated	Consume half	Sell just under half

Cluster Name	TVA Proportion Off-farm	Innovation Score	Future Plans Score
Innovative Cash Croppers	None	Highest score	Strong desire to increase activities
Innovative Multi taskers	Just over half	Close to highest score	Medium desire to increase activities
Traditional Subsistence	None	Lowest score	Weak desire to increase activities
Traditional Cash Croppers	None	Middle score	Weak desire to increase activities

Table 3. A qualitative explanation of combined clusters. The variables used are also found in tables 1 and 2, where the same scaling has been applied Based on data provided by the International Livestock Research Institute.

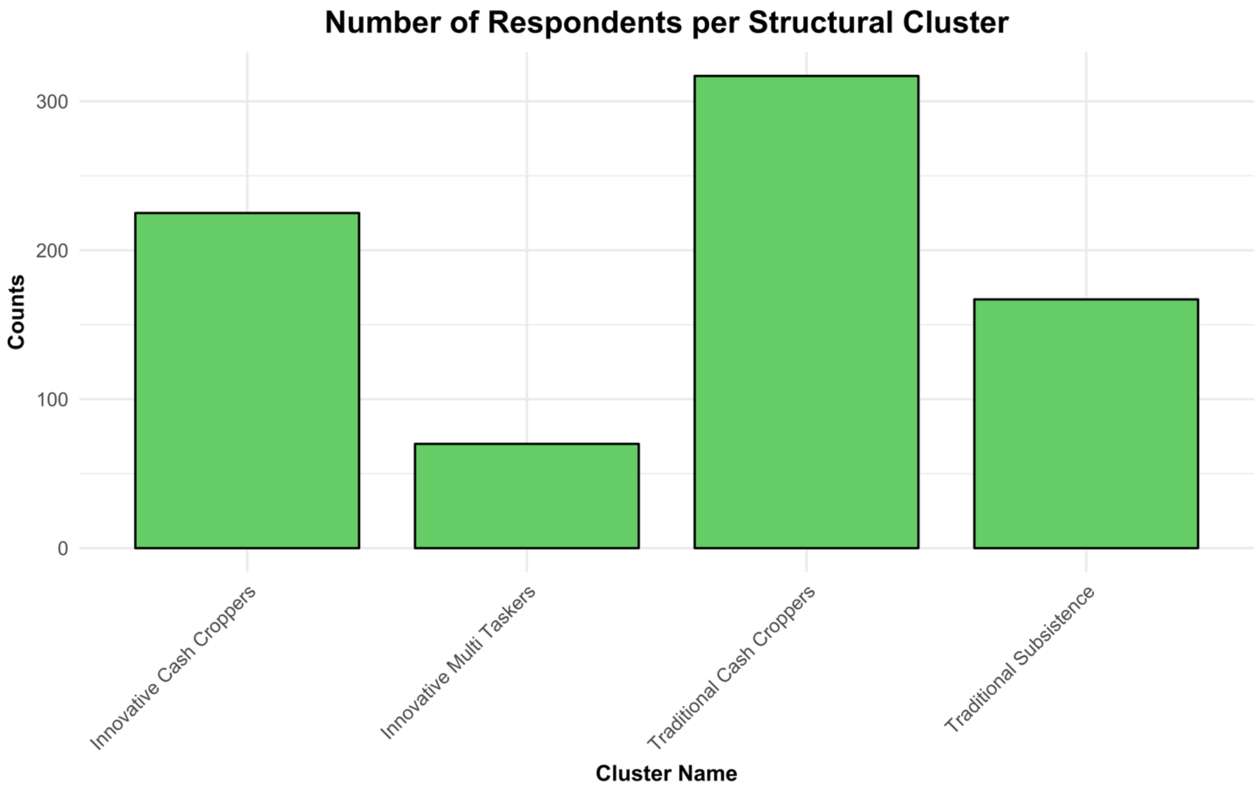

Figure 15. A bar-plot displaying the number of respondents belonging to each combined cluster. Based on data provided by the International Livestock Research Institute.

5.4.3 Can Combined Clusters Predict High Adoption for the Whole Population?

Grouping farmers by their structural and motivational characteristic made it possible to investigate their adoption characteristics. Both adoption strength and adoption rate, as defined in section 4.3.5, were investigated.

From figure 16, which shows the differences in adoption rate for the whole population of combined clusters, it can be seen that traditional cash croppers had the highest adoption rate, at 92 percent. Traditional subsistence, innovative cash croppers and innovative multi taskers had adoption rates of 87, 86 and 80 percent respectively.

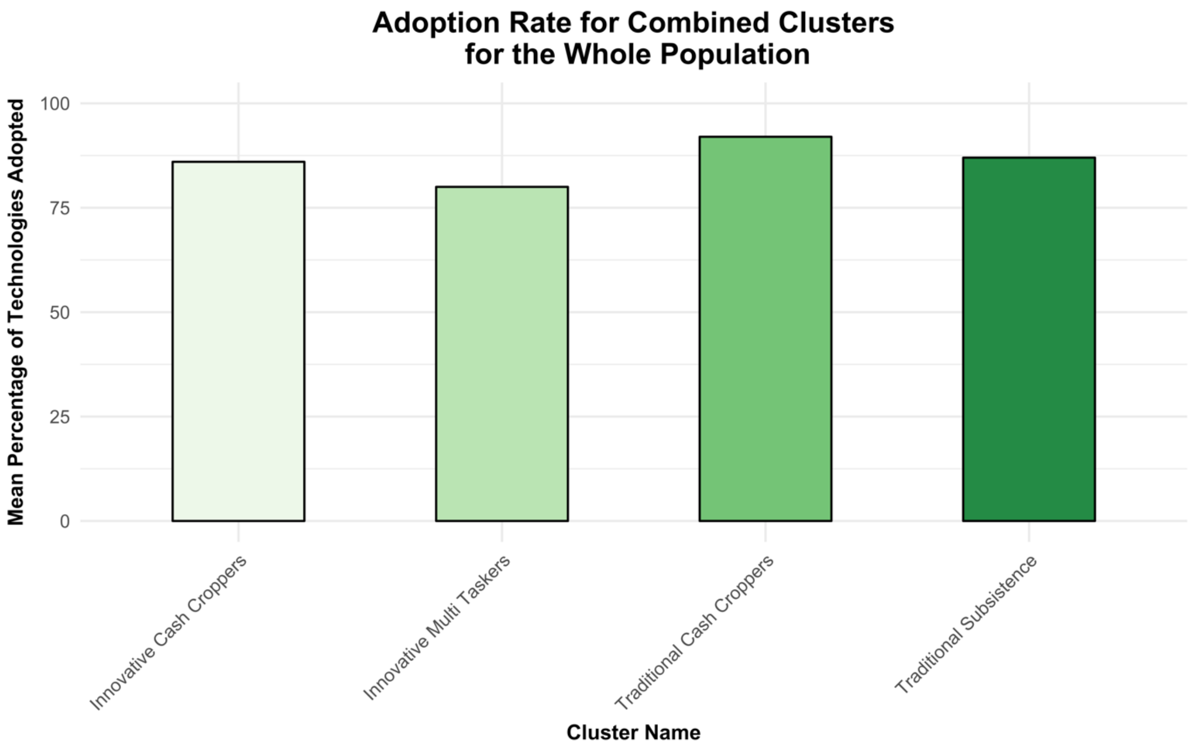

Figure 16. The mean adoption rate of each combined cluster when the examining the population as a whole. Based on data from the International Livestock Research Institute.

Figure 17 shows the adoption strength score of each combined cluster when the population was taken as a whole. In this case, the more innovative farmers had the higher scores. Innovative cash-croppers had the highest adoption strength score of 0.71.

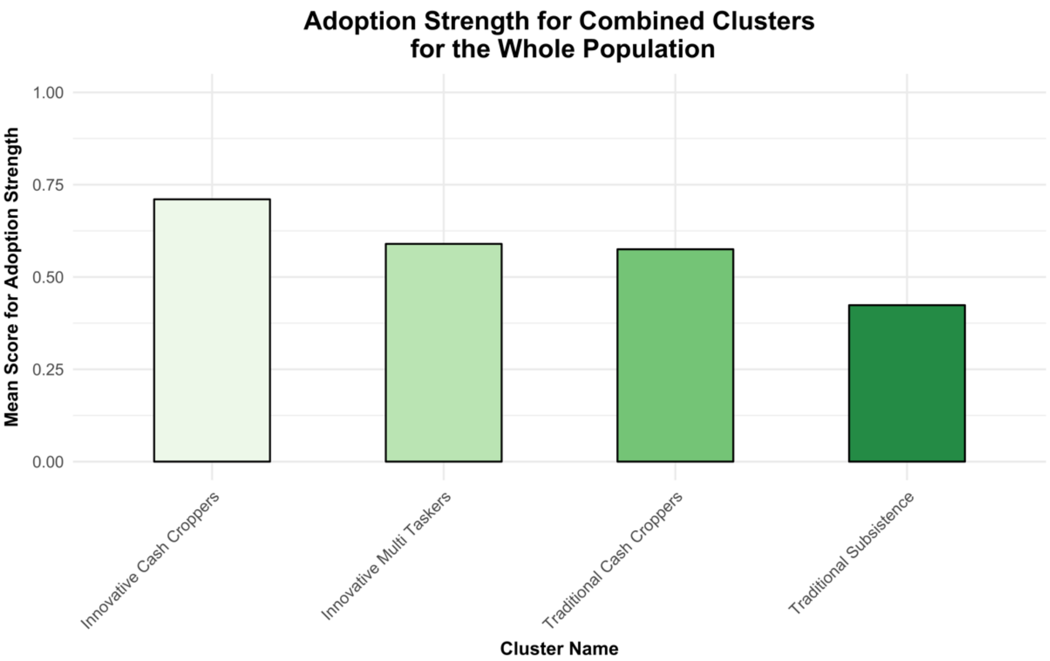

Figure 17. The mean adoption strength of each combined cluster when the examining the population as a whole. Based on data from the International Livestock Research Institute.

To conclude this subsection, combined clusters were effective for predicting high adoption rates and high adoption strength when the population was taken as a whole. For adoption rates, the highest scores were found in traditional cash-croppers. For adoption strength, the highest scores were found in the innovative cash-cropper cluster.

5.4.4 Can Combined Clusters Predict High Adoption in the Lower Wealth Categories?

Section 5.4.3 illustrated how combined clusters can predict adoption rates and adoption strength when examining the whole population. To see whether combined clusters could be used to identify a group of high adopting farmers, in the lowest wealth quartiles, the population was divided into FA quartiles.

Combined clusters effectively identified farmers with high adoption rates for the lower, lower-middle and upper FA quartiles. While they effectively identified farmers with a high adoption strength for the lower, lower-middle and upper-middle FA quartiles.

Figure 24 shows the differences in adoption rate for the lower FA quartile. In this case, innovative multitaskers had the highest adoption rate, at 96 percent. While traditional cash croppers, innovative cash croppers and traditional subsistence farmers had adoption scores of 94, 88 and 85 respectively.

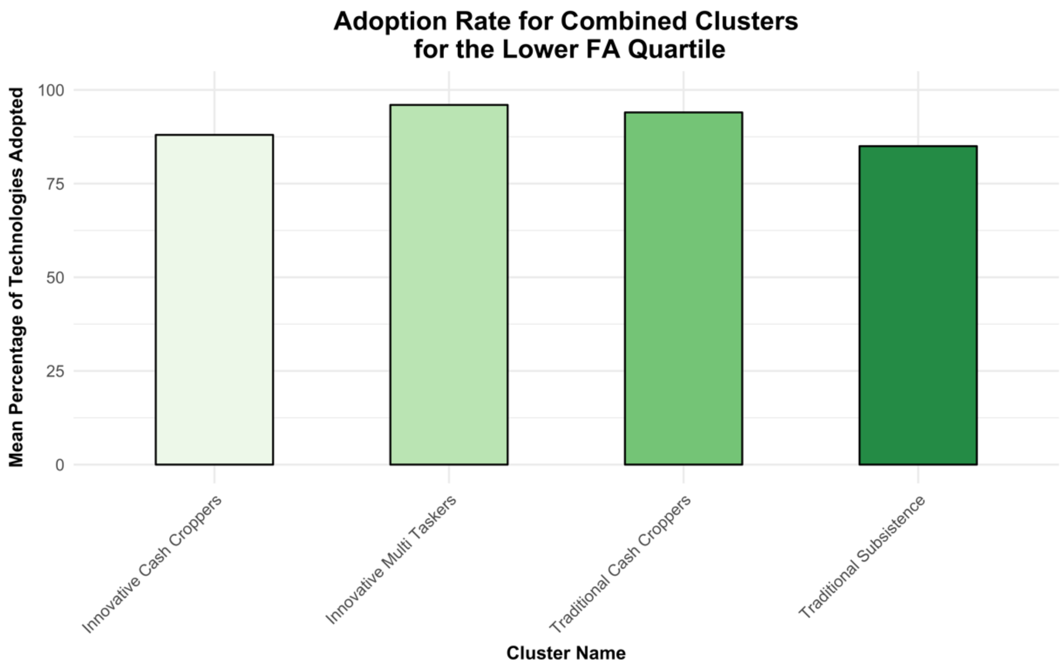

Figure 18. The mean adoption rate of each combined cluster when the examining lower FA quartile. Based on data from the International Livestock Research Institute.

For the other two FA quartiles, where significant differences in adoption rate were observed, there is a different trend. For lower middle and upper FA quartiles, traditional cash croppers had the highest adoption rate, at 94 and 91 percent respectively. This relationship is visualised in figures 19 and 20.

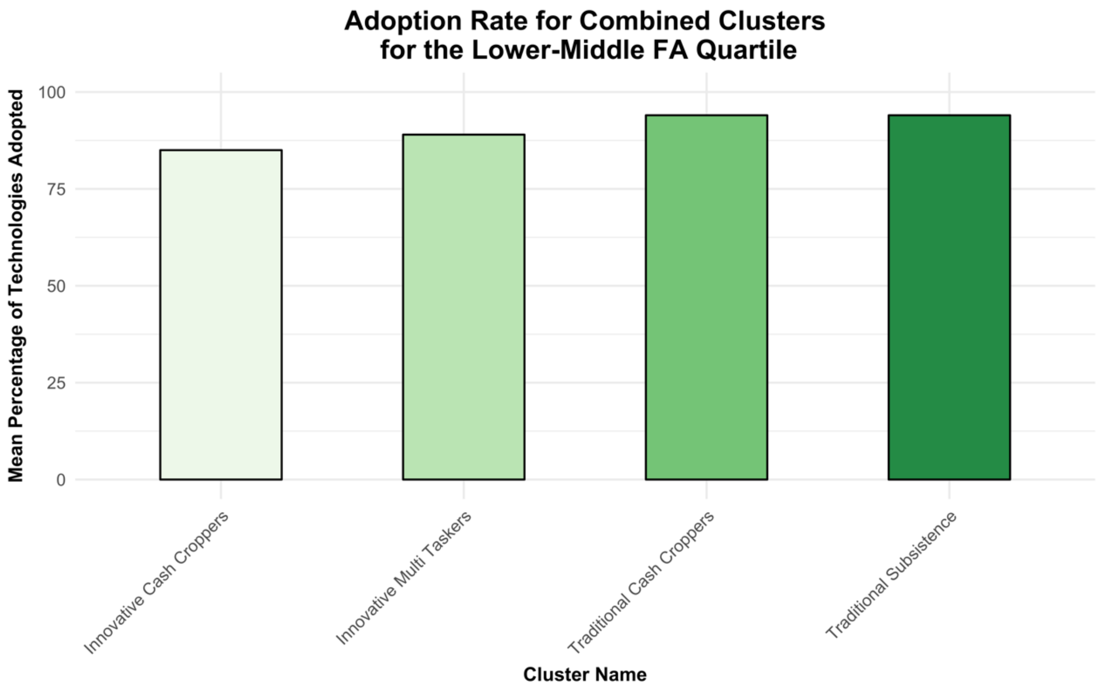

Figure 19. The mean adoption rate of each combined cluster when the examining lower-middle FA quartile. Based on data from the International Livestock Research Institute.

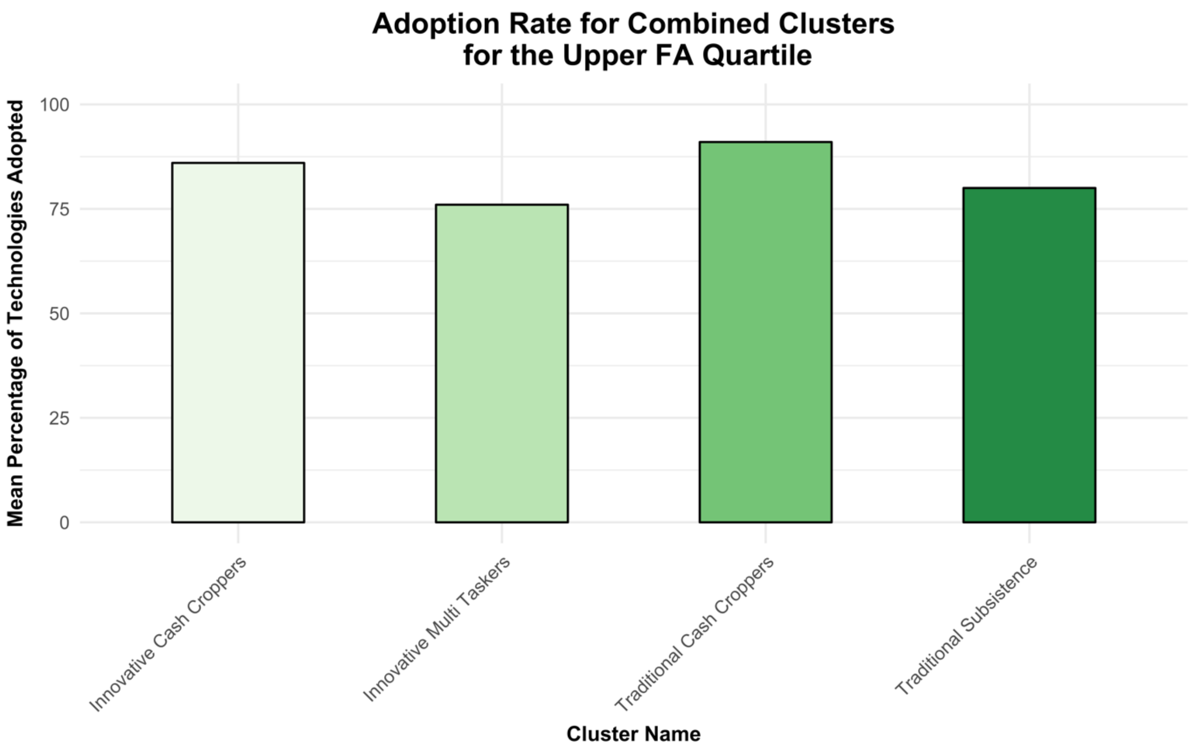

Figure 20. The mean adoption rate of each combined cluster when examining the upper FA quartile. Based on data from the International Livestock Research Institute.

When examining adoption strength scores a different trend emerges. As with motivational clusters, for combined clusters, the more innovative farmers had a higher adoption strength score. This relationship was significant for the lower, lower-middle and upper-middle FA quartiles.

Figure 21 shows the differences in adoption strength score for combined clusters in the lower FA quartile. In this case, innovative multi-taskers had a higher adoption strength score at 67 percent. Innovative cash croppers had a similarly high score at 64 percent.

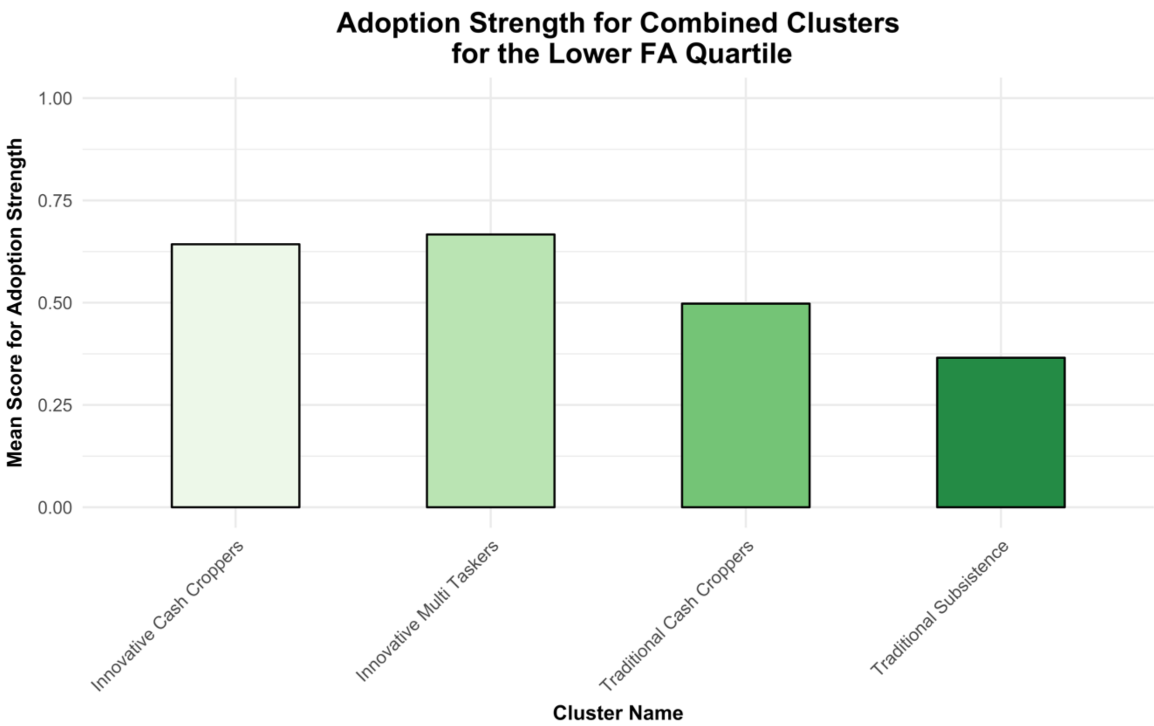

Figure 21. The mean adoption strength of each combined cluster when examining the lower FA quartile. Based on data from the international livestock research institute.

Figure 22 and figure 23 show the differences in adoption strength score for the lower-middle and upper-middle FA quartiles respectively. In both cases, higher adoption strength scores were observed for innovative cash croppers. For all the three wealth quartiles where significant differences in adoption strength score were observed, traditional subsistence farmers consistently had the lowest score. Additionally, in the lower-middle FA quartile, as depicted in figure 22, innovative multitaskers had a particularly low score in innovation.

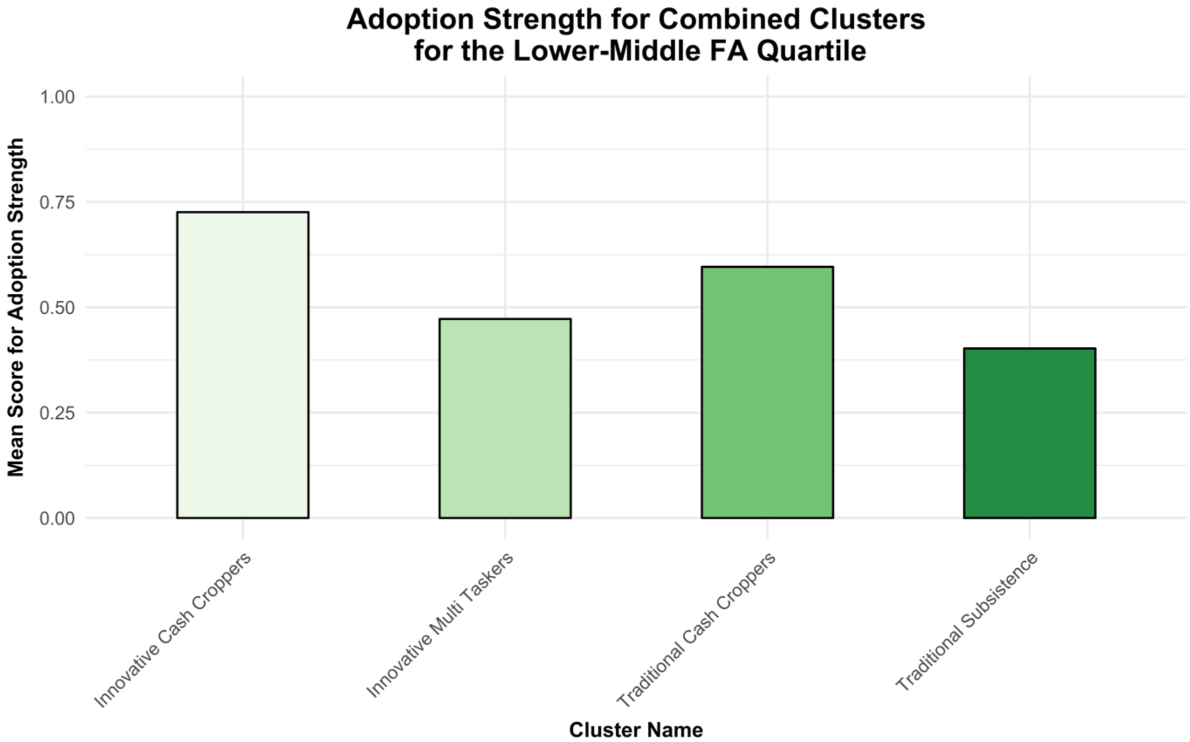

Figure 22. The mean adoption strength of each combined cluster when examining the lower-middle FA quartile. Based on data from the international livestock research institute.

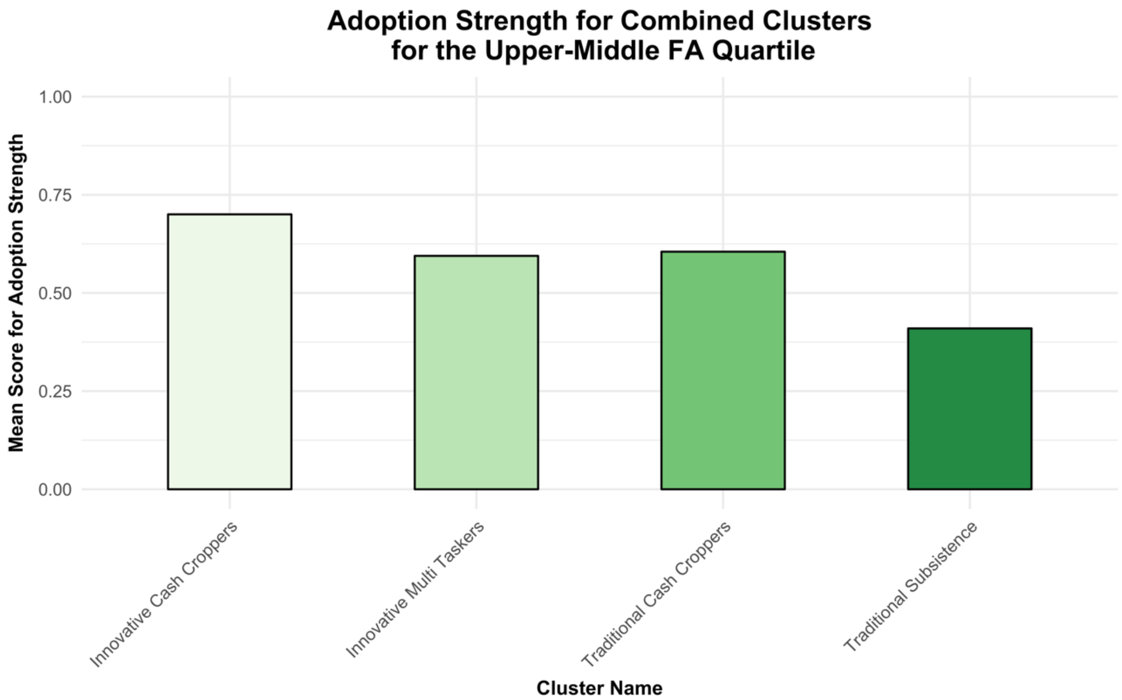

Figure 23. The mean adoption strength of each combined cluster when examining the upper-middle FA quartile. Based on data from the international livestock research institute.

5.5 A Summary of the Adoption Characteristics for Three Types of Clustering

Cluster Type	Variable	FA Quartiles where adoption scores between clusters varied significantly	Cluster with highest Score	Score
Structural	Adoption Rate (%)	Whole Population	Crop orientated	91%
		Upper	Crop orientated	90%
	Adoption Strength (0-1 scale)	Whole Population	Market Orientated	0.63
Motivational	Adoption Rate (%)	Whole Population	Wannabe Innovator	92%
	Adoption Strength (0-1 scale)	Whole Population	Highly Innovative	0.70
		Lower	Highly Innovative	0.63
		Lower-middle	Highly Innovative	0.70
		Upper-middle	Highly Innovative	0.73
		Upper	Moderate Traditional Committed	0.8
Combined	Adoption Rate (%)	Whole Population	Traditional Cash Croppers	92%
		Lower	Innovative multi-taskers	96%
		Lower-middle	Traditional Cash Croppers	94%
		Upper	Traditional Cash Croppers	91%
	Adoption Strength (0-1 scale)	Whole Population	Innovative cash croppers	0.71
		Lower	Innovative multi-taskers	0.67
		Lower-middle	Innovative cash croppers	0.73
		Upper-middle	Innovative cash croppers	0.70

Table 4. A table summarising the results of section 5.2. Column 1 indicates which type of cluster was being investigated, column 2 indicates which variable is being investigated, column three includes the FA quartiles where there was a significant relationship between the clusters and the variable, column four indicates which specific cluster had the highest score for this FA quartile and column 5 indicates the score. Based on data provided by the International Livestock Research Institute.

To summarise the results pertaining to clustering and adoption patterns, all three types of cluster could effectively predict adoption rates and adoption strength when the population was taken as a whole. Structural clusters were not an effective way to predict high adoption rates and high adoption strength for the lower FA quartiles. Motivational structures could not predict high adoption rates in the lower FA quartiles, however, they could predict high adoption strength for all individual FA quartiles. Moreover, combined clusters could predict high adoption rates and high adoption strength for the lower FA quartiles.

5.6 Catalysts and Barriers to Adoption According to Respondents

Identifying high adopting farmers in the lower wealth quartiles is important to ensure the distribution of innovations is efficient. However, to further understand the process of adoption it is useful to develop a deeper understanding of the reasons why farmers adopt and the barriers preventing them from further adoption. Through an examination of the data, it was made clear that there was almost no variation, in motivators or barriers to adoption, across wealth quartiles or across each type of cluster. As a consequence, the results have been provided in the form of a whole population overview.

Figure 24 illustrates the reasons, stated by respondents, for the adoption of their selected innovations. "Complementary" refers to whether or not the innovations provided complemented innovations which were already being used. The majority of respondents stated that the advice provided to them by the Africa RISING program had affected the decision to adopt. The fact that the technology satisfied their needs played less of a role for respondents, however, this reason was still given by the majority.

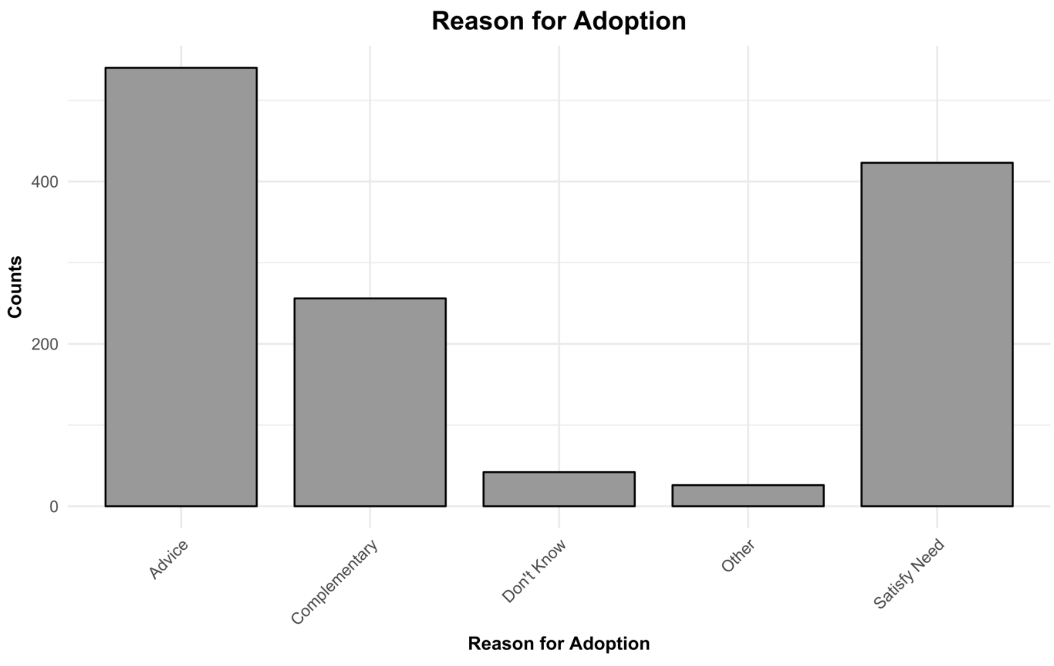

Figure 24. The frequency of reasons, given by respondents, for adopting various technologies. Based on data from the international livestock research institute.

Figure 25 outlines the reasons, given by respondents, preventing further adoption. “Already a lot” refers to the idea that farmers already had enough technologies and, hence, had no desire to adopt more. Across all clusters, and wealth quartiles, the majority of respondents stated that a lack of support had diminished their motivation to adopt more technologies in the future. However, a precise definition of “support” was lacking. Additionally, many stated that a lack of land reduced the likelihood that they would adopt more technologies in the future.

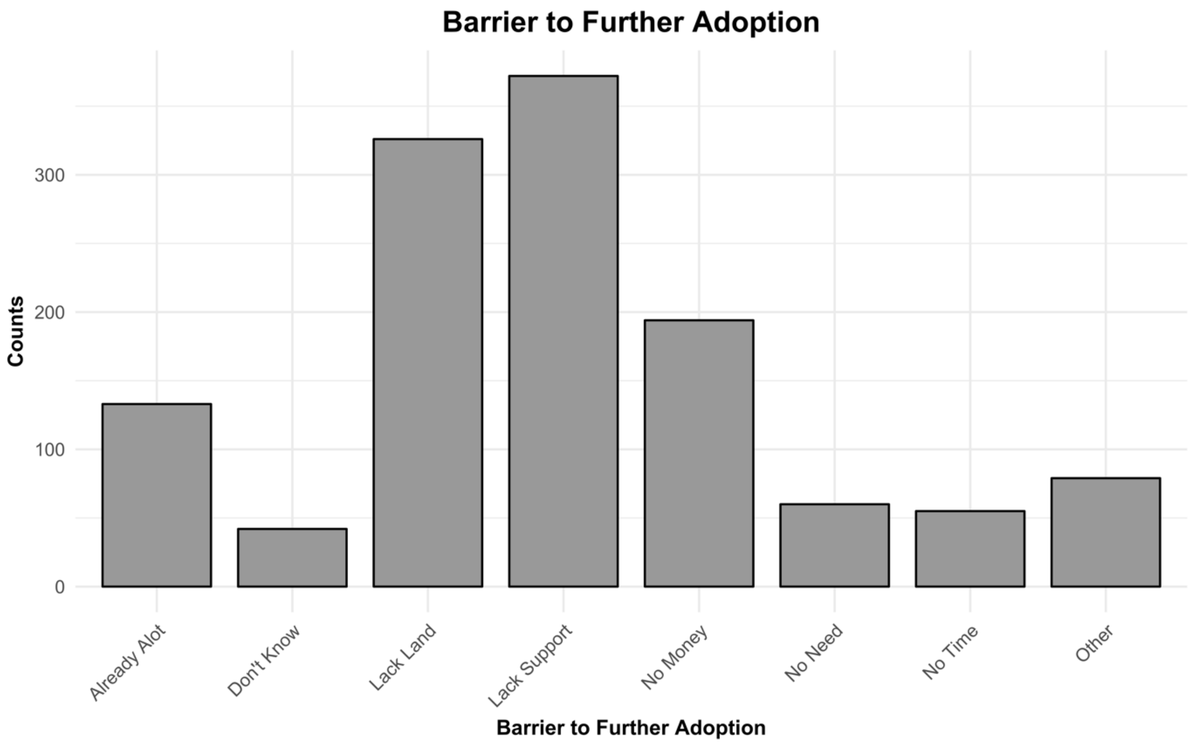

Figure 25. The frequency of reasons, given by respondents, for why they did not adopt more technologies. Based on data from the international livestock research institute.

6. Discussion

After having outlined the findings of this investigation, this section discusses their significance. There are two important factors to discuss. Firstly, it is essential to discuss the quality and distribution of the data, this has an effect on the conclusions reached and their validity. Secondly, there is a need to discuss how these findings relate to the theory outlined in section 2. As these two factors are so heavily interlinked, they are discussed simultaneously.

As was outlined in the results, there were significant differences between the adoption rates of structural clusters when the population was taken as a whole. However, the significance of this relationship broke down when individually examining lower, lower-middle and upper-middle FA quartiles. This suggests that structural clustering is not an effective tool for identifying high adopting farmers in the lower wealth quartiles, one of the key aims outlined in section 3. Moreover, the same can be said for predicting adoption strength, there were only significant differences in adoption strength when looking at the population as a whole. However, the evidence outlined in this investigation is insufficient to completely dismiss the use of structural clustering to identify high adopting farmers. As discussed in section 4, the respondents of the RHoMIS survey had already been selected based on structural typologies developed by Africa RISING. This may have skewed the data, an idea supported by the fact that the sample had a particularly high adoption rate of 88 percent. Secondly, it is possible that a larger sample size would reveal significant differences in adoption rate among the lower wealth quartiles. This is simply due to the nature of statistical testing, a larger sample will provide a more reliable confirmation of hypotheses.

Likewise, the differences in adoption rates among motivational clusters were only significant when examining the whole population. However, there were no significant differences in adoption rates, between motivational clusters, when examining individual FA quartiles. As a result, there is insufficient evidence to suggest that motivational clusters, developed by using the techniques in this investigation, can be used to target farmers with high adoption rates in individual wealth quartile. Once again, a larger sample which has not been selected based on structural typologies could reveal that significant differences in adoption rates across various wealth quartiles.

In contrast, motivational clusters proved to be a very effective tool for predicting the adoption strength for the whole population and for individual wealth quartiles. This is despite the size of the sample and the biases introduced by the initial structural typologies of the Africa RISING program. As was outlined in section 2.3, the commitment with which farmers implement the use of a new innovation is essential for the horizontal diffusion of said innovation. As a result, for the lower, lower middle and upper middle quartiles, identifying farmers in the highly innovative cluster could increase the probability that the beneficiaries of interventions strongly integrate an innovation into their farming practices. For the upper FA quartile, this investigation suggests identifying farmers belonging to the moderate traditional committed cluster. Identifying these clusters would sustainably intensify production for beneficiaries and those who adopt the technologies through horizontal diffusion. As was discussed in section 2, this sustainable intensification can help achieve the goals outlined by the human development theory.

This study also determined that, unlike purely structural and purely motivational clusters, the results from using combined clusters are much more promising for predicting both adoption rates and adoption strength. Despite the problems with the sample, previously outlined in this section, statistically significant differences in the adoption rates of combined (structural and motivational) clusters have been observed for: the whole population, the lower FA quartile, the lower-middle FA quartile and the upper FA quartile. As can be seen in table 4, when examining the whole population, traditional cash croppers had the highest adoption rate at 92 percent. For the lower FA quartile, innovative multi-taskers had the highest adoption rate at 96 percent. For the lower-middle FA quartile, traditional cash croppers once again had the highest adoption rate, at 94 percent. This is also the case for the upper FA quartile, where the adoption rates were 91 percent for traditional cash croppers. These significant differences suggest that combined clusters are a viable method for targeting farmers, belonging to the lower FA quartiles, who are more likely to adopt. Interestingly, the results suggest that development programs may need to adopt a more nuanced approach to identify farmers, targeting different clusters depending on the FA quartiles in which farmers belong. This supports the discussion by Methorst *et al.* (2017, 16), which suggested that conventional structural typologies did not account for the heterogeneity of small farms.

Counterintuitively, for the whole population, the lower FA quartile and the upper FA quartile, the highest adoption rates were found in a cluster with a relatively low score in innovation. This suggests that more traditional farmers can be convinced to use a particular innovation once they have proven it to be effective. For the lower, lower middle and upper middle FA quartiles, there were significant differences in adoption strength among combined clusters. For the population as a whole, for the lower middle FA quartile and the upper FA quartile, innovative cash-croppers had the highest score for adoption strength. While for the lower FA quartile, innovative multi-taskers had the highest score for adoption strength. Once again, this suggests the need for a more nuanced approach, identifying different clusters for each FA quartile. For all quartiles, the highest adoption strength was found in clusters which had a high innovation score. This suggests that the innovation indicator is useful for predicting commitment to particular technologies, which in turn can catalyse the horizontal diffusion of agricultural innovations. In short, the use of combined clusters to identify high adopters, both related to strength and adoption rates, is promising. Using this method to identify farmers could lead to the more efficient use of resources and increase the probability that innovations will diffuse horizontally between smallholder farms. This in turn could lead to more widespread sustainable intensification which can help achieve the goals of human development.

Although the results show the promise of a more nuanced approach to smallholder typologies, this investigation is only the first step. Firstly, as demonstrated in section 2.3, local government policy can have a significant effect on the adoption and horizontal diffusion of agricultural innovations. The farmers analysed in this investigation were all subject to the same agricultural policy. As a result, it was much easier to create typologies based on relative differences between farmers. In contrast, cross-country comparisons between smallholder farmers could reveal that these particular typologies do not accurately predict high adoption rates or high adoption strength for farmers subject to different agricultural policies. If this is the case however, it only reinforces the idea that a more nuanced approach must be used to account for the heterogeneity of smallholder farms. Moreover, farmers analysed in this investigation had already been identified by the Africa RISING program. In order to more rigorously validate, or invalidate, the use of the three typological methods, it would be beneficial to survey farmers both before and after interventions have been provided. This is certainly achievable, considering the fact that only 12 questions were used in order to identify farmers' motivations. The collection of more data, relating to farmers' motivations, will increase the probability that accurate typologies are used.

To improve future data collection, it is important to note that the data used had limitations which impeded the development of more descriptive typologies. Firstly, TVA calculations do not consider the products obtained from livestock, for example cheese. When respondents were asked about innovation, the questions focused on how much effort respondents put into innovating. This does not take into account the reasons for the effort, or lack of effort, the farmers make to innovate. An alternative question in the survey asked whether respondents though innovation was important, however, the responses given to this question were limited to "yes" and "no". The responses to this question showed little variation. For future surveys, it may prove beneficial to ask the same question with a more specific scale of answers, such as: "not important"; "slightly important"; "very important". This would minimise the variation caused by the fact that some farmers had inadequate means to innovate. The adoption strength was determined from the question which asked whether respondents intended to use more of the innovation provided, with the options: "less"; "same"; "more"; "much more". These responses were given a numerical ranking from which it was possible to create a normalise score (on a scale from 0-1). More specific and quantifiable questions could be asked, allowing the data to reveal to what extent the innovation will be used in the future. Moreover, the motivational clusters used in this investigation rely solely on farmers' attitudes. As stated in section 2, Meijer *et al.* (2014, 1) demonstrate that adoption rates are also influenced by farmers' knowledge and perceptions. To further test the potential of motivational typologies, it would be useful to develop a set of questions which provide insight into how farmers perceive particular innovations and their knowledge about these innovations

Additionally, in section 5.6 it was demonstrated that farmers adopted new innovations primarily based on advice, while the greatest barrier to further adoption was the lack of support for farmers. It was found that these principals were applicable to all wealth quartiles as well as types of cluster. These findings confirm the ideas presented by Nowak (1987, 202), discussed in section 2.3, which outline how farmers need access to agronomic and economic information in order to adopt. As a consequence, research and development should continue to develop more effective ways of informing farmers about innovations as well as reducing the perceived economic risks associated with adoption.

Finally, this investigation only seeks to address a small part of the adoption process. There is a huge variety of factors, from government policy to the provision of information, that affects adoption rates and adoption strength. Researchers should continue to advance in all fields relating to the adoption process, allowing development programs to efficiently use resources to achieve the goals of human development

7. Conclusion

This investigation highlighted the importance of the human development theory, the participatory approach and the sustainable development approach. In setting out to achieve some of the goals laid out in these concepts, this investigation examined the challenges facing the poorest parts of the population. It was outlined that SSA experiences some of the worst poverty globally. By examining the demographics of SSA, it was concluded that the rural poor are some of the worst affected. The majority of the rural poor in SSA are involved in agriculture to some extent. Considering the growing population, increasing demand for produce and a greater strain on natural resources, it was made clear that there was an urgent need to address agricultural production. Using the Green revolution as an example, it was made evident that sustainable intensification was an effective tool for addressing the issues of the worlds' rural poor.

With such a clear connection between development and agriculture, it was necessary to identify the barriers to sustainable intensification. A literature review indicated that there was currently a low adoption rate for distributed agricultural innovations. Several reasons for this were identified. One of the main reasons involved the perceived risk associated with adopting new innovations and a lack of institutional support to reduce this perceived risk. However, it was described how making changes to such an inertial system would take significant time. One alternative involves a more thorough understanding of the diffusion of innovations between farmers. A group of farmers, known as early adopters, are the first to try an innovation. If this innovation is successful, it is more likely to be passed on to late adopters. The success of an innovation requires commitment from those who try it first. This made clear the need to target the most committed farmers at the first stages of intervention.

As was outlined in section 2.3, typologies are a common tool for identifying potential high adopters. However, conventional methods to develop typologies based on the structural characteristics of the farm, such as the amount of land, education level and the crops grown, do not help construct a holistic understanding of adoption among farmers. It was outlined, based on more recent literature, that considering the personal motivations of farmers would help account for the heterogeneity of small farms. Hammond *et al.* (2017) had tested motivational typologies by comparing them to structural typologies and found that there was no correlation between the two. However, motivational typologies had not been compared to actual adoption rates. Based on the fact that agricultural interventions favoured wealthier farmers and that motivational typologies had not been tested against actual adoption rates, this investigation sought to test whether a group of high adopting farmers, in the lowest FA quartiles, could be found using three types of typology: purely structural; purely motivational; a combination of structural and motivational.

In order to empirically test the use of these typologies, this investigation used data provided by ILRI, collected in connection with the Africa RISING program, funded by USAID. Various indicators for the three types of cluster were created. Using PAM clustering, ANOVA significance tests and the Chi square test, the three types of cluster were compared to adoption rates and adoption strength. A significant relationship was found between adoption rates, as well as adoption strength, and structural clusters. However, this relationship was only valid when examining the whole population and there was insufficient evidence to suggest that structural cluster could provide useful predictions for adoption rate or adoption strength within any individual FA quartile. For the case of the whole population, it was found that crop orientated farmers had the highest adoption rate and market orientated farmers had the highest adoption strength, according to the structural cluster definitions outlined in table 1. A significant relationship was found between adoption rate, as well as adoption strength, and motivational clusters. For adoption rate, motivational clusters only provided useful predictions when the population was taken as a whole, where wannabe innovator farmers had the highest adoption rate. However, for adoption strength, motivational clusters provided useful predictions for all FA quartiles. For the lower, lower-middle and upper-middle FA quartiles, highly innovative farmers had the highest adoption strength. While for the upper FA quartile, moderate traditional committed farmers had the highest adoption strength. A significant relationship was found between adoption rate, as well as adoption strength, and combined clusters when taking the population as a whole. For adoption strength, significant relationships were also found for the lower, upper middle and upper FA quartiles. The clusters with the highest adoption rates were traditional cash croppers for the whole population, the lower FA quartile and the upper FA quartile. Innovative multi-taskers had the highest adoption rate for the lower middle FA quartile. Innovative cash croppers had the highest adoption strength when the population was taken as a whole but also for the lower middle and upper middle FA quartiles.

The findings of this investigation at the very least suggest that farmers' personal motivations should be taken more seriously when creating typologies for targeted interventions. This investigation, however, did outline the need for more rigorous testing in order to create more robust typologies. There is a chance that the differences in agricultural policy between countries will mean that farm typologies will have to be adapted for each country. However, this can only be confirmed through further data collection and research. The sample used in this investigation had already been identified using structural typologies, however increased adoption rates have still been observed despite this bias, supporting the need for further investigation into the use of motivational and combined typologies. The results of this investigation also confirm the need for further support for innovating farmers, as lack of support has been identified as a significant barrier to adoption.

With further research into how farmers' personal motivations can be used to increase adoption rates it is possible that first-stage interventions will become more successful. This can contribute to further horizontal diffusion of agricultural innovations which in turn will lead to greater sustainable intensification. If this is combined with increased support for innovating farmers agricultural development programs will be able to more efficiently achieve some of the goals outlined by human development theory, participatory approaches and sustainable development approaches.

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Appendix

Structural Cluster Numeric

Cluster Name	Head Education Level	Land Cultivated	Crop Diversity	Livestock Diversity
Market orientated farmers	0.3333	0.07352941	0.3043478	0.5000000
Educated off-farm	0.6667	0.04411765	0.2173913	0.5000000
Subsistence	0.3333	0.08823529	0.4782609	0.3333333
Crop Orientated	0.3333	0.05882353	0.2608696	0.3333333

Cluster Name	Livestock Orientation	TVA Proportion Consumed	TVA Proportion Sold	TVA Proportion Off-Farm
Market orientated farmers	0.3696	0.353762	0.60940	0.0000
Educated off-farm	0.0166	0.230800	0.24739	0.5225
Subsistence	0.3484	0.745400	0.23670	0.0000
Crop Orientated	0.0000	0.500000	0.47370	0.0000

Appendix 1. A table quantitatively describing the traits of structural clusters. All variables are on a 0-1 scale. Based on data from the International Livestock Research Institute.

Motivational Cluster Numeric

Cluster Name	Innovation Score	Commitment to Agriculture Score	Future Plans Score
Traditional Uncommitted	0.5111	0	0.00000
Wannabe Innovators	0.8333	0	0.11111
Highly Innovative	0.9333	0	0.88890
Moderate Traditional Committed	0.6444	1	0.22220

Appendix 2. A table quantitatively describing the traits of motivational clusters. All variables are on a 0-1 scale. Based on data from the International Livestock Research Institute.

Combined Cluster Numeric

Cluster Name	Head Education Level	Land Cultivated	Crop Diversity	Livestock Diversity
Innovative Cash Croppers	0.3333	0.07352941	0.2608696	0.5000000
Innovative Multi taskers	0.6667	0.04411765	0.1739130	0.5000000
Traditional Subsistence	0.6667	0.08823529	0.5217391	0.1666667
Traditional Cash Croppers	0.3333	0.05882353	0.3043478	0.3333333

Cluster Name	Livestock Orientation	TVA Proportion Consumed	TVA Proportion Sold
Innovative Cash Croppers	0.3393	0.435734	0.52964
Innovative Multi taskers	0.0596	0.230800	0.24168
Traditional Subsistence	0.3490	0.653250	0.32122
Traditional Cash Croppers	0.0000	0.500000	0.47368

Cluster Name	TVA Proportion Off-farm	Innovation Score	Future Plans Score
Innovative Cash Croppers	0.000	0.9333	0.7778
Innovative Multi taskers	0.5263	0.9056	0.5000
Traditional Subsistence	0.000	0.7222	0.2222
Traditional Cash Croppers	0.000	0.7748	0.2222

Appendix 3. A table quantitatively describing the traits of combined clusters. All variables are on a 0-1 scale. Based on data from the International Livestock Research Institute.